

# Introduction to Vision and Robotics: Assignment 1

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## 1 Introduction

For this assignment, our task was to identify and track three 'cars' or 'robots' in a sequence of images taken using a webcam. The images have a relatively uniform background, and the cars have distinct red, green and blue colours, and identical shapes with an arrow indicating their facing. Only one car of each colour is present, and the cars are visible in most but not all frames. The two obvious approaches to detection are one based on the shapes, and one based on the colours of the cars. We chose to use colours, since an approach based on shape would need to use colour to disambiguate the cars in any case. Our approach makes use of several simple image filtering techniques, a search for colour maxima across rows and columns, thresholding and region segmentation to separate the cars from their background, and region centroids and centres of mass to identify the facing of the cars.

## 2 Methods

### 2.1 Initial Processing

The first part of the algorithm, summarised in Figure 1, processes each image to minimise variations both between datasets and across each image. First, the image is blurred using a gaussian kernel of width 5; this removes some of the noise in the image which would cause trouble in later stages. Next, the rgb value of each pixel is normalized; this corrects for variations in illumination across the image. At this stage, the green channel is modified by subtracting 0.2 times the blue channel. This is because the colours of the cars are not a pure value in a single channel; in particular, the blue car shows up brightly on the green channel. This simple operation is equivalent to finding a new "green car channel" attuned particularly to the green car. If the cars were other colours, such as cyan, magenta and yellow, we could have constructed dedicated channels for each car; but in this case a simple tweak to the green channel was enough to disambiguate the cars. Finally, each colour channel is scaled so that the minimum and maximum values present in the channel map to 0 and 1. This helps the thresholding after detection.

### 2.2 Detection

The detection algorithm works on a single image at a time, and identifies the most likely location of the red, green and blue cars. The algorithm estimates the location of each car in the image using the corresponding colour channel. For the red car for instance, it looks at the red channel, and computes the maximal value for each row, and for each column. It convolves each of these to reduce noise, and finds the maximum along the rows and maximum along the columns.

Although this point is likely to be within the robot, it is not necessarily at its center. To get a better estimate of the center of the robot, we find the neighbourhood along each axis which stays within 90

Finally, we compute a threshold for separating the robot from the background in the colour channel; we choose a value of 0.75 times the maximal value.

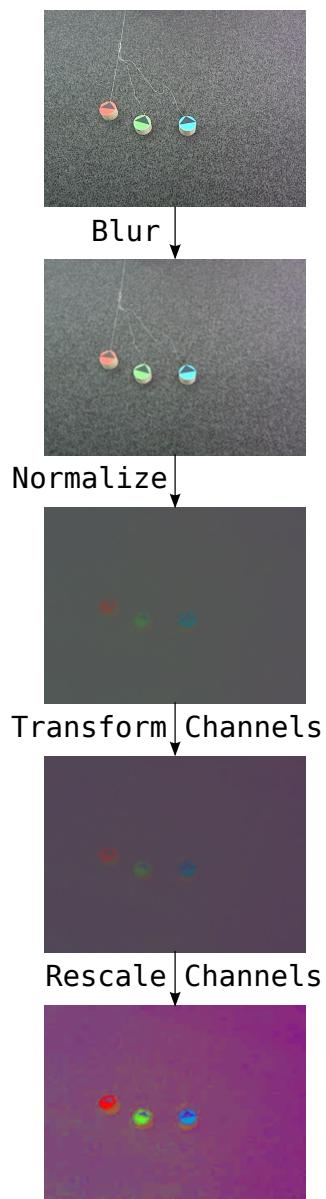


Figure 1: Image Processing Pipeline

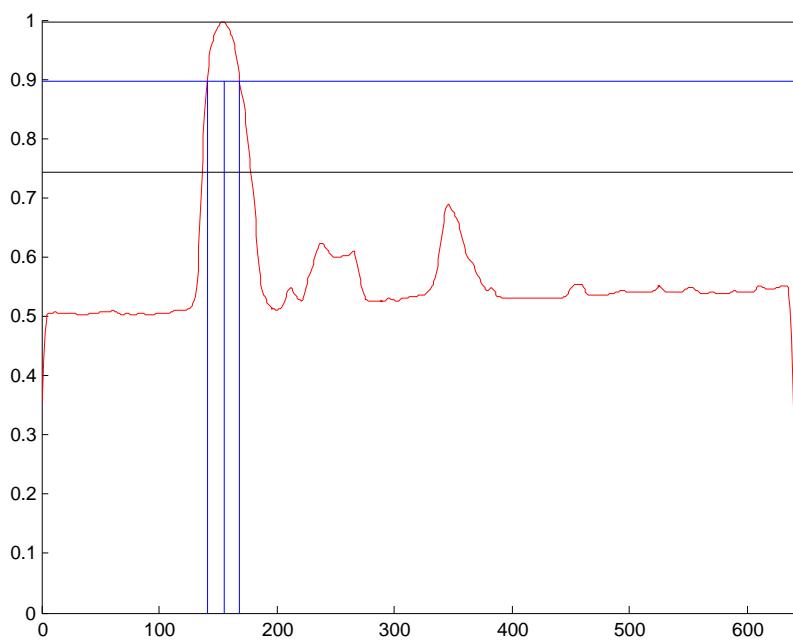


Figure 2: Red value maxima along each image column

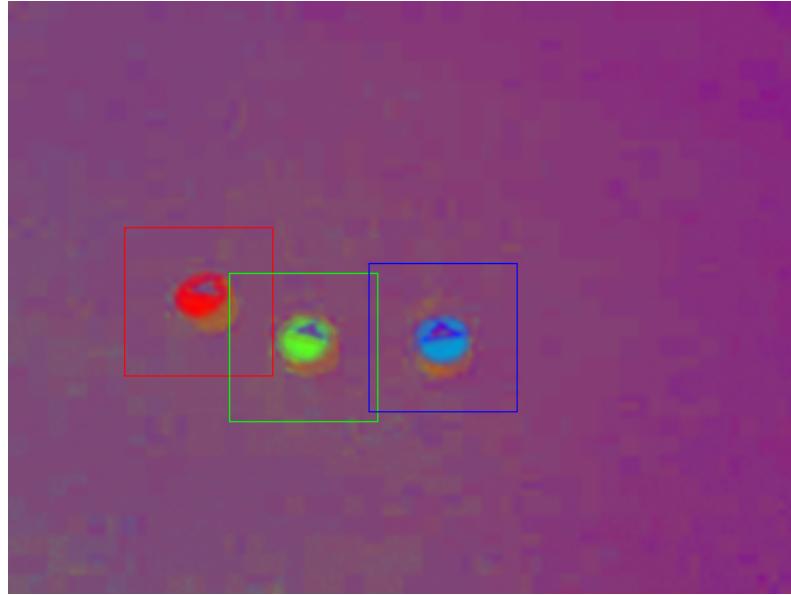


Figure 3: Initial bounding box

For each channel, the algorithm then takes a 120x120 bounding box around the estimated robot centre, thresholds it using the computed threshold, and passes the image to the next stage for finer-grained processing.

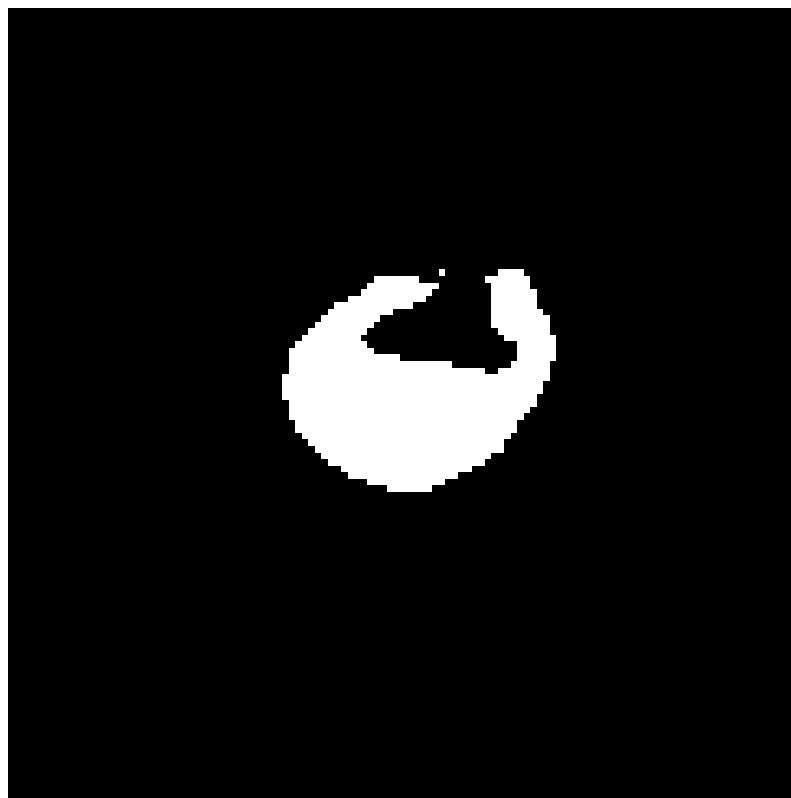


Figure 4: Binary image (Red channel)

## 2.3 Linking Algorithm

The linking algorithm is used to link together detections of a single robot in consecutive frames. Since the images provided in the datasets are RGB, the linking algorithm has been developed to run on each of the three colour channels respectively.

The algorithm is shown in *Figure 5*. Initially, the image on the  $k^{th}$  iteration will have been split into three colour channels of red, green and blue respectively. Each colour channel is represented as a separate image and each image has been clipped to a dimension of  $120 \times 120$  in the detection algorithm. This enables a more accurate bounding box to be calculated for each robot as there will be less image noise in the clipped image.

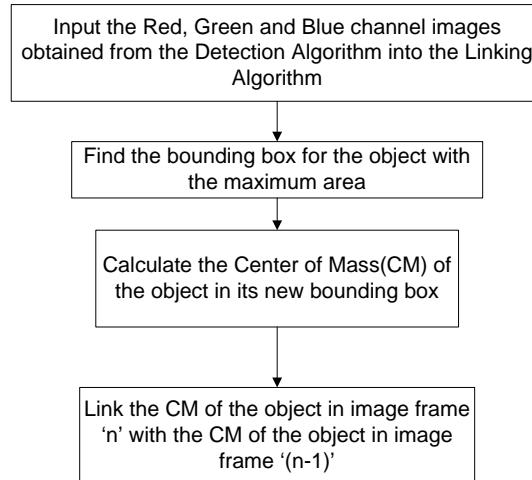


Figure 5: The algorithm developed to link detections of the robot in consecutive frames

### 2.3.1 Finding the Bounding Box

The bounding box of each robot is calculated using the function *calcBoundingBox*. A flow diagram of the function can be seen in *Figure 6*. This function calculates the bounding box for each robot as well as the box's corresponding centroid in each of the three colour channels respectively.

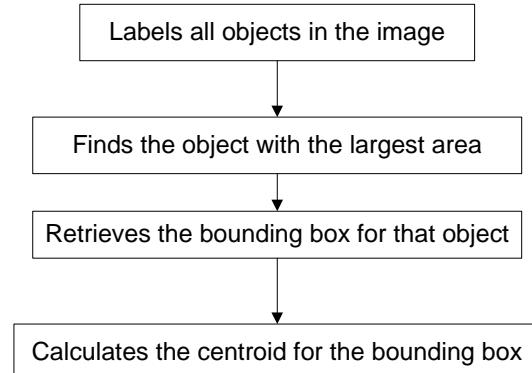


Figure 6: The bounding box calculation for each robot

An excerpt from the *calcBoundingBox* function is shown below.

```

1 %Excerpts from the bounding box calculation
2
3 %Label the image. The labelled image is labelX
4 [labelX, numXBlobs] = mybwlabel(TImgX);
5
6 %Calculate the area for each object found in 'labelX'
7 allBlobAreas = [];
8 for i=1:numXBlobs
9     [rows,cols,vals] = find(labelX==i);
10    blobSize = sum(vals);
11    allBlobAreas = [allBlobAreas blobSize];
12
13 end
14
15 %Find the object with the maximum area in the image
16 [maxBlobArea, index] = max(allBlobAreas);
17
18 if HaveToolbox==0
19 %Without using the image toolkit, extract the bounding box
20 [rows,cols,vals] = find(labelX==index);
21 x1 = min(cols);
22 x2 = max(cols);
23 y1 = min(rows);
24 y2 = max(rows);
25 end

```

Each image is labelled using the *mybwlabel* function as seen in the code excerpt. This will identify all of the objects in the image and assign a set value to each pixel associated with a specific object.

The object with the largest area is then identified. A bounding box is subsequently calculated for the object with the largest area (I.e. the largest number of labelled pixels). This is achieved using the *find* Matlab function which identifies the largest object and stores each pixel belonging to the object with its respective row and column position. This is then used to determine the bounding box of the object.

The object will then be surrounded by its corresponding bounding box. The centroid of this bounding box is then calculated. This algorithm is performed on each of the three clipped images corresponding to the three respective colour channels.

It must also be noted that due to bad lighting or image noise, a robot may not be detected in an image frame. This has been catered for in the *calcBoundingBox* function. If the maximum calculated area of an object in the image is 0, then it is assumed that an object has not been detected and the frame is skipped.

### 2.3.2 Calculate the Center of Mass

Once a bounding box for each robot has been determined, the center of mass of the robot needs to be calculated in relation to this new bounding box. This is achieved by utilising the *calcBoundingBoxCM* function.

The algorithm initially calculates the area of the object within the bounding box using *Equation 1*. This value is used to determine the center of mass of the object within the bounding box.

$$A = \Sigma_r \Sigma_c P_{rc} \quad (1)$$

The center of mass of the object is then determined using *Equation 2*.  $(\hat{r}, \hat{c})$  are the row and column coordinates of the center of mass of the object respectively.

$$(\hat{r}, \hat{c}) = \left( \frac{1}{A} \Sigma_r \Sigma_c r P_{rc}, \frac{1}{A} \Sigma_r \Sigma_c c P_{rc} \right) \quad (2)$$

### 2.3.3 Linking and Plotting

The final step in the linking algorithm is to link the object in image frame  $n$  with the object in the previous image frame  $(n - 1)$ . A criteria needs to be developed in order to define when this ‘linking’ of objects should occur.

The criteria has been defined as follows. It has been previously mentioned that each image has been separated into its R,G and B channels. The R,G,B images have also been cropped into  $120 \times 120$  dimension images. Within these cropped images, the object with the largest area of pixels in each channel is chosen to represent the robot. For example, the object with the largest area of red pixels in the red channel cropped image, represents the red robot. Based on this assumption, the largest objects detected in adjacent image frames, in the same colour channel, are connected. This is a safe assumption as the largest concentration of red, green and blue pixels are usually associated with the red, green and blue robots respectively, once the images have been cropped to a  $120 \times 120$  dimension.

The center of mass of the red, green and blue robots are stored in ‘linker’ arrays as shown below. The links are plotted on the estimated background image at the end of the program.

```

1 %*****
2 %To link tracks on the estimated background image
3 XLinkerR = [XLinkerR trueCMXR];
4 YLinkerR = [YLinkerR trueCMYR];
5 XLinkerG = [XLinkerG trueCMXG];
6 YLinkerG = [YLinkerG trueCMYG];
7 XLinkerB = [XLinkerB trueCMXB];
8 YLinkerB = [YLinkerB trueCMYB];

```

## 2.4 Identifying Robot Orientation

Once the positions of the robots have been identified, the next step is to determine the direction in which the robot is currently travelling. The orientation of the robot is identified by an arrow that points in the robot’s current direction of movement. At this stage it is important to define the difference between the meaning of an arrow and an arrowhead in this report. An arrow refers to the vector calculated to point in the robot’s current direction of movement as shown in *Figure 7*. An arrowhead refers to the arrow attached to the face of the robot.

The orientation algorithm ultimately connects the center of mass of the robot to the centroid of the bounding box surrounding the robot as seen in *Figure 8*. Due to the structure of the robot, the robot’s center of mass is found just below the centroid. Connecting the center of mass to the centroid will generally result in an accurate vector describing the robot’s orientation.

The algorithm initially receives the center of mass coordinates of the robot as well as the bounding box centroid as shown in the code below. Using these values, the algorithm then defines vectors  $DR$ ,  $DG$  and  $DB$  for each of the three colour channels. By normalising these vectors using *Equation 3*, unit vectors are obtained and are then scaled to create the arrows pointing in the direction of the robots current orientation. These arrows are then plotted on the current image frame using a third-party function called *plot\_arrow*.

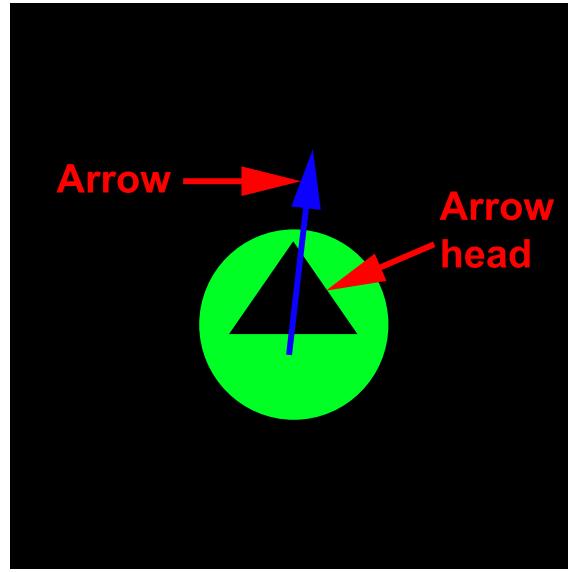


Figure 7: The definition of an arrow and an arrowhead

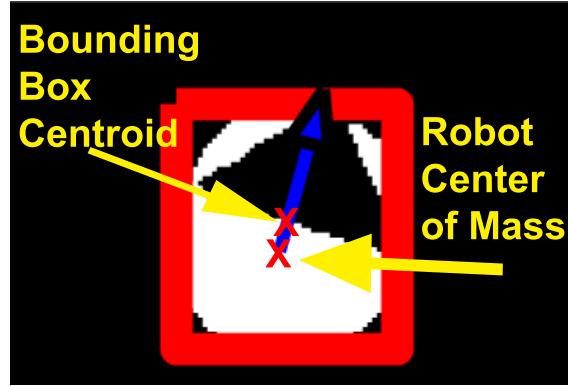


Figure 8: Connecting the center of mass of the robot to the bounding box centroid to determine the robot's orientation

$$D_x = \frac{D_x}{\|D_x\|} \quad (3)$$

```

1 %Define unit vectors in the direction of the bounding
2 %box centroid for each of the rgb channels respectively
3 CenterMassR = [CenterMassXR CenterMassYR];
4 DR = (CentroidR - CenterMassR);
5
6 CenterMassG = [CenterMassXG CenterMassYG];
7 DG = (CentroidG - CenterMassG);
8
9 CenterMassB = [CenterMassXB CenterMassYB];
10 DB = (CentroidB - CenterMassB);
11
12 %Calculate the unit vectors for each channel
13 DR = DR/norm(DR);
14 DG = DG/norm(DG);
15 DB = DB/norm(DB);

```

```

16
17 %*****
18 %Excerpt of code for plotting the arrows connecting the
19 %centroids and center of mass of each robot
20 plot_arrow(trueCMXR,trueCMYR, trueCentroidBBXR+30*DR(1),trueCentroidBBYR+30*DR(2)...
21 , 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColRArrow,...
22 'facecolor',LineColRArrow);
23 hold on
24 plot_arrow(trueCMXG,trueCMYG, trueCentroidBBXG+30*D(1),trueCentroidBBYG+30*D(2)...
25 , 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColGArrow,...
26 'facecolor',LineColGArrow);
27 hold on
28 plot_arrow(trueCMBB,trueCMBY, trueCentroidBBXB+30*DB(1),trueCentroidBBYB+30*DB(2)...
29 , 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColBArrow,...
30 'facecolor',LineColBArrow);

```

## 2.5 Background Estimation

Estimation of the background image required the implementation of a variety of different image processing techniques. This is because the datasets provided presented a number of challenges. One such challenge was that of removing robots that were stationary for a significant portion of a frame sequence. This prevented the simple implementation of a median filter to calculate the background image. This is due to the fact that objects that are stationary for a large subset of the frames will be incorporated into the median and subsequently into the background image.

Therefore, in order to solve this problem, an algorithm has been developed to calculate the background image, regardless of stationary robots being in large subsets of the frame sequence.

The background estimation algorithm consists of three main functional blocks. These blocks are *Channel Processing*, *Region Erasing and Filling* and *Median Filtering* respectively. The *Channel Processing* block receives an image frame and processes the image. This includes blurring, normalising, separating the image into its three channels, subtracting the blue channel from the green channel and renormalising the image. This creates an image that is ready for *Region Erasing and Filling*. In order to implement this functional block, the image channels for the current frame are input into a function called *eraseRegion*. A code snippet of the function is shown below.

```

1 function [Out] = eraseRegion(Img, C, Size)
2     Out = Img;
3     %Find the pixels on the vertices of the bounding box
4     %surrounding the robot. top=t, bottom=b, left=l, right=r
5     t = max(1, C(1) - Size/2);
6     b = min(size(Img, 1), C(1) + Size/2);
7     l = max(1, C(2) - Size/2);
8     r = min(size(Img, 2), C(2) + Size/2);
9     %Find the average of the four pixels at the vertices of the
10    %bounding box
11    Avg = Img(t, l, :) + Img(t, r, :) + Img(b, l, :) + Img(b, r, :);
12    Avg = Avg / 4;
13    %Replace the image segment (I.e. the robot) with the average
14    %of the four pixels
15    for y = t:b
16        for x = l:r
17            Out(y, x, :) = Avg;
18        end
19    end

```

This function calculates the average value of the pixels found at the corner vertices of the bounding boxes surrounding each robot as shown in *Figure 9*. The corner pixels are averaged across all three colour channels and are stored in the variable *Avg*. All of the pixels in the region

containing the robot are then filled with this new average value to produce the image shown in *Figure 9*. This is applied to each of the robots in the image.

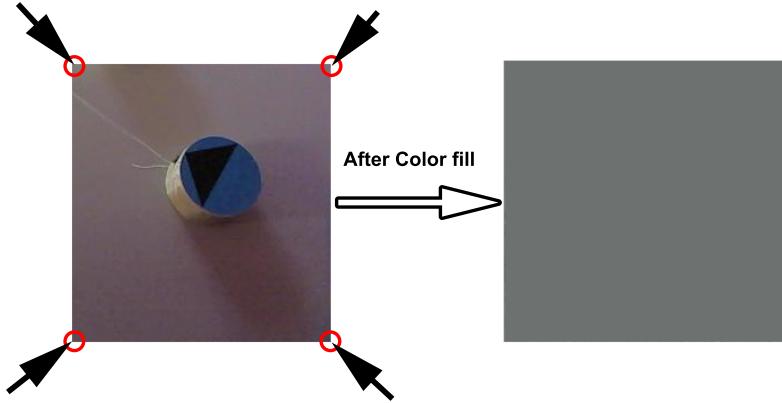


Figure 9: The corner pixel intensities are averaged and are then used to fill the region of the image containing the robot

The *Region Erasing and Filling* functional block is implemented on the three image frames that are used for background estimation. The reason three image frames have been chosen is because this is the minimum number of frames required to effectively use a median filter which is utilised in the *Median Filtering* functional block. In addition to this, using a small number of frames to compute the median minimises the algorithm's processing time. The median of the three images is subsequently computed to produce an estimation of the background image.

### 3 Results

This section details the performance of the image detection algorithms. The algorithms are generally able to detect the robot and determine its orientation. There are some situations where the algorithm cannot achieve this objective. An analysis of the estimated background images are also conducted.

#### 3.1 Robot Detection

The robot detection algorithm was able to detect the robots in most of the datasets. It did however miss a number of detections on dataset 7. One of the primary reasons for this is that certain image frames in dataset 7 contain areas of dark pixels. These pixels may be a result of bad lighting when the frame was captured. It may also be due to JPEG artefacts that were generated when the frame was captured and compressed [?]. The dark pixels become a problem when the image frame is normalised. Normalisation amplifies the intensity of dark pixels causing sharp peaks to form. These peaks are, on occasion, mistaken for robots and the incorrect object is identified in the image frame. An example of this can be seen in *Figure 10* where an area of highly saturated green pixels have resulted in an incorrect detection. The bounding box identifying the object in the green colour channel is very compact indicating that the algorithm has selected the high intensity pixels rather than the green robot as shown in *Figure 11*.

Dataset 1 also generated some incorrect detections. These errors occurred as a result of the red robot leaving the image frame. As the robot leaves the frame, the algorithm looks for a set of red pixels that correspond to a red robot. Since the robot is not present, the algorithm identifies the next largest area of red pixels as being the red robot. This is incorrect and causes the results

Table 1: Results obtained from trying to detect whether or not a robot is in an image frame

Type	Correct Detection			Missed Detection			Incorrect Detection		
	Red	Green	Blue	Red	Green	Blue	Red	Green	Blue
Dataset 1	83	93	95	0	0	0	12	2	0
Dataset 2	95	95	95	0	0	0	0	0	0
Dataset 7	64	57	64	30	30	30	1	8	1
Dataset 8	95	95	95	0	0	0	0	0	0
Dataset 10	95	95	95	0	0	0	0	0	0

shown in the table. An example of this is shown in *Figure 12* and *Figure 13* respectively. In this example, the red robot has left the scene and a group of red pixels, as shown in *Figure 13*, have been incorrectly defined as being the red robot resulting in an incorrect detection. Another reason for incorrect detections may be due to a non-uniform background as seen in *Figure 10*. This causes problems, especially after normalisation, adding unwanted high intensity pixels.

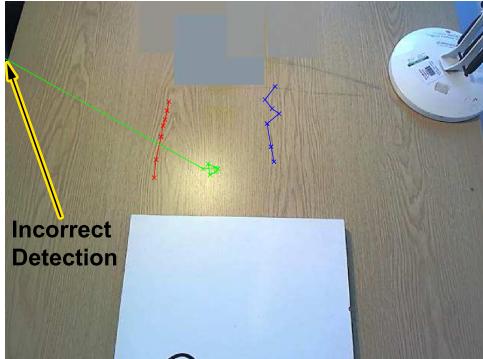


Figure 10: An incorrect detection of the green robot. This results in a broken track

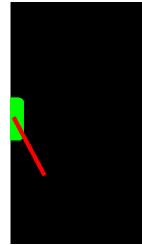


Figure 11: The incorrect detection of the green robot due to a small region of highly saturated pixels.

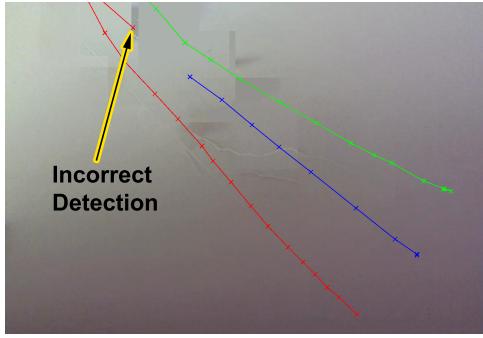


Figure 12: An incorrect detection of the red robot. This track has been linked to the track of the blue robot creating an incorrect track.



Figure 13: The incorrect detection of the red robot as shown in the red channel binary image.

### 3.2 Linking Robot Tracks

As detailed in Section 3.2, a linking algorithm for the robots has been developed. This algorithm was tested on a variety of datasets and the results are tabulated in Table 2. This table details the number of *Correct tracks*, *Incorrect Tracks* and *Broken Tracks*. A *Broken Track* has been defined

as the lack of a connection between two adjacent tracks.

The linking algorithm performed well on datasets 2, 8 and 10 recording no incorrect detections. However, dataset 1 had a large number of incorrect and broken tracks, especially on the red channel. This is a result of the red robot leaving the image frame as detailed in *Section 3.1*. An example of this is shown in *Figure 12* and *Figure 13* respectively. In this example, the red robot has left the scene and a group of red pixels, as shown in *Figure 13*, have been incorrectly defined as being the red robot. This results in an incorrect linkage between two tracks.

Dataset 7 also has a large number of broken tracks and this is as a result of the highly saturated pixels and bad lighting in the image frames as detailed in *Section 3.1*.

Table 2: Results obtained from linking robot tracks on a variety of different datasets

Type	Correct Tracks			Broken Tracks			Incorrect Tracks		
	Red	Green	Blue	Red	Green	Blue	Red	Green	Blue
Dataset 1	83	93	95	12	2	0	0	0	0
Dataset 2	95	95	95	0	0	0	0	0	0
Dataset 7	64	57	64	30	30	30	1	8	1
Dataset 8	95	95	95	0	0	0	0	0	0
Dataset 10	95	95	95	0	0	0	0	0	0

Another situation occurs whereby the robot tracks are incorrectly linked. As seen in *Figure 10*, the green robot track has been incorrectly linked to the left hand side of the image frame. This is due to a pixel or group of pixels,  $p_i$  having a peak intensity that is higher than the peak intensity of the green robot's pixels. Thus the group of pixels,  $p_i$ , will be selected as being the robot object rather than the robot itself. This occurs due to the normalisation of the image as very dark pixels are normalised to high intensity values causing an incorrect linkage between tracks.

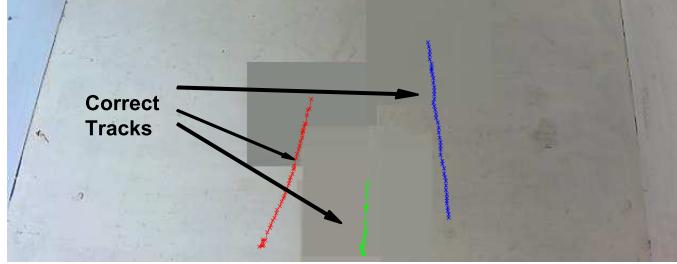


Figure 14: An example of correct robot tracks

### 3.3 Robot Orientation

The orientation of the robots was tested on a variety of different datasets and the results for each dataset is presented in *Table 3*. There are a number of scenarios whereby the orientation is incorrectly determined causing the arrows to point in incorrect directions. This created a number of missed and incorrect directions as shown in *Table 3*.

An incorrect direction is defined as an arrow pointing at least  $45^\circ$  away, in either direction, from the central vertex of the robot's arrowhead as shown in *Figure 15*. The algorithm is unable to detect that the arrow is pointing in an incorrect direction. An example of this situation is seen in *Figure 16*.

A missed direction is defined as an arrow oriented in an incorrect direction relative to the robot's current direction of motion. However, here the algorithm is able to identify this incorrect

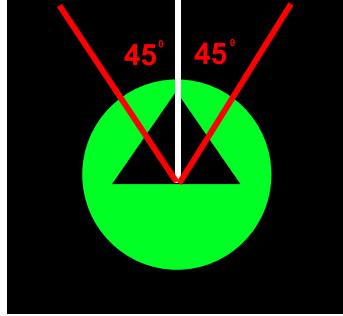


Figure 15: The boundaries for a correct detection

orientation and subsequently marks the arrow with a red colour as seen in *Figure 16*.

Table 3: Results obtained from determining which direction the robot is facing

Type	Correct Direction			Missed Direction			Incorrect Direction		
	Red	Green	Blue	Red	Green	Blue	Red	Green	Blue
Dataset 1	89	83	93	6	6	2	0	6	0
Dataset 2	89	77	90	5	8	0	1	10	5
Dataset 7	57	44	44	32	40	32	6	11	19
Dataset 8	94	84	92	0	0	0	1	11	3
Dataset 10	91	81	89	0	2	4	4	12	2

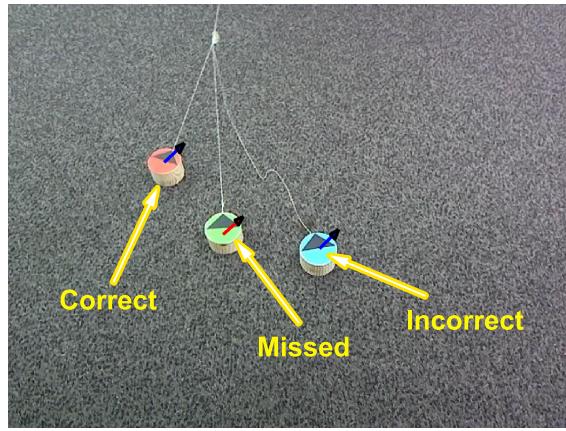


Figure 16: Examples of correct, incorrect and missed arrow orientations respectively

*Figure 17* is an example of one of the shortcomings of the current orientation algorithm. As can be seen in the figure, the bounding box of the robot has been placed around the lower segment of the robot's face. It has completely ignored the arrowhead attached to the robot's upper segment. This is because the upper and lower segments of the robot are separated as there is no

4 or 8 connectivity present between the pixels. The algorithm thus sees the lower segment of the robot as having a larger area and subsequently surrounds that image portion with a bounding box.

This creates another problem. The centroid of the bounding box is now found below the center of mass of the robot as seen in the figure. Therefore, when the direction arrow is constructed, the arrow points in the incorrect, and in this case, opposite, direction of the robot's movement.

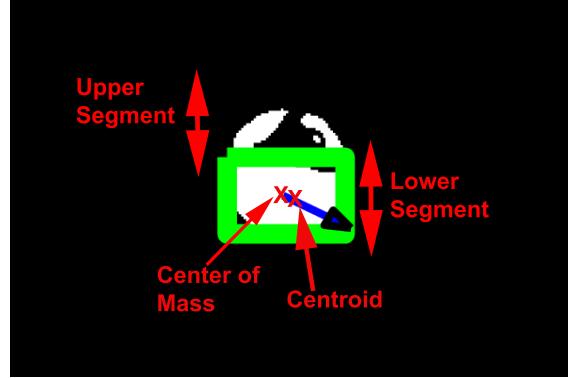


Figure 17: Examples of correct, incorrect and missed arrow orientations respectively

### 3.4 Background Images

This section analyses the background images produced using the Background Estimation Algorithm detailed in Section 3.4. As can be seen in each of the estimated backgrounds from *Figure 18* to *Figure 21*, the presence of the robots have caused a slightly blurred effect on each of the images. This is because the corner pixel averaging, detailed in Section 3.4, does not create a perfect representation of the background colour for every pixel that it replaces.

Backgrounds with less texture, such as *Figure 18*, gave better estimation results. This is because these backgrounds have less colour variation and so the corner pixel averaging technique created a much better representation of the background colour for each pixel.



Figure 18: The estimated background image of the first dataset provided for image processing

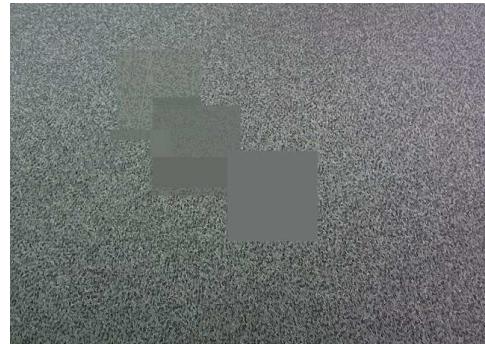


Figure 19: The estimated background image of the second dataset provided for image processing

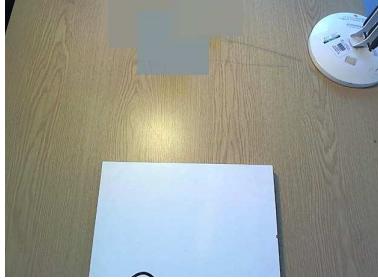


Figure 20: The estimated background image of a new test dataset



Figure 21: The estimated background image of a new test dataset

## 4 Discussion

This section determines the success of the above-mentioned image processing algorithm. In addition, the limitations and problems present in the current design are discussed, as well as future improvements that could be implemented to enhance the algorithm's performance.

### 4.1 Success Evaluation

The image processing algorithm performs particularly well on uniform backgrounds. It is able to detect the robot's in almost every frame and maintains a fairly accurate estimate of the robot's current orientation. Textured backgrounds do interfere with processing each robot's orientation. This is partly due to the normalisation procedure performed on each image frame.

The algorithm encounters a problem when a robot leaves the image frame as was the case in dataset 1. Incorrect detections result and incorrect tracks are formed on the image frame. The algorithm also struggles with pixels of high intensity that do not form a part of the robot. If these pixels are the same colour as the robot, they are then incorrectly chosen to represent the robot in the specified image frame.

One of the advantages of the algorithm is that it efficiently processes the images at a relatively high speed. This is due to the efficient implementation of the algorithm in Matlab. This is an important feature if the algorithm is to be exposed to larger datasets.

### 4.2 Limitations and Problems

A prominent problem presented during this project was that of Image-encoding noise [? ]. The datasets provided for the project were of a JPEG file type. JPEG images contain compression artefacts which represent data lost due to the compression of the image [? ]. These artefacts presented a problem as important image information was lost that could have been useful during image processing. The artefacts themselves were also problematic after the image was normalised, producing pixels of high intensity, which was disruptive to the robot detection process.

### 4.3 Future Improvements

The *normChannel* Matlab function currently performs contrast stretching on each image. This technique is used to stretch the range of pixel intensity values which ultimately increases the contrast of the image. However, this technique is sensitive to pixel outliers [? ]. The algorithm does not currently take this into account. Doing so in a future implementation would result in an improvement in image contrast.

The current algorithm used to determine the orientation of the robot could also be improved. An alternative approach would be to calculate the center of mass of the arrowhead situated on the robot. Connecting the robot's center of mass with the arrowhead center of mass may provide an improved estimate of the robot's current orientation.

There are also alternative techniques to detecting the robot's in a given image. Once such technique is that of region splitting [? ]. This technique treats an image as a single region and iteratively splits the image into sub-regions that share the same, or similar, characteristics. This is achieved using a split-and-merge algorithm. As the process iterates, regions that contain similar characteristics are also merged together. This is an effective way to detect different regions as well as objects in an image.

Another effective method that can be used to detect the robots is edge detection. By taking a Laplacian of a Gaussian (LoG), it is possible to detect the edges of an object [? ]. This technique could be applied to the robot images to effectively detect the robot edges.

## 5 Conclusion

The image processing algorithm developed to detect robots in an image sequence has been detailed. Various techniques such as normalisation, blurring, contrast stretching and histogram smoothing have been implemented in this algorithm. Various sub-algorithms have been defined such as robot detection, linking tracks in successive image frames as well as determining the robot's current orientation. The algorithm was able to maintain near perfect performance in detecting robots. However, if a robot leaves an image frame or there are highly saturated pixels of the same colour as the robot, then the algorithm struggles to detect the robot creating incorrect tracks. An estimated image of the background has been processed. Blurred patches are present on some of the background images, but this can be minimised. Various improvements have also been suggested such as region splitting for detecting the robots as well as finding the center of mass of the arrowhead in order to create a better orientation arrow.

## References

## APPENDIX A

### A.1 Program Code

#### A.1.1 Read Image Sequences into Matlab

```
1 function Imgs = myreadfolder(Folder, Count)
2     % Load a first image to use for format and size
3     TestImg = myreadimg(Folder, 1);
4     % zero-initialise an input matrix of the right size and type
5     Imgs = zeros(size(TestImg,1), size(TestImg,2), size(TestImg,3), Count, class(TestImg));
6     % read in all the images
7     for I = 1:Count
8         Imgs(:, :, :, I) = myreadimg(Folder, I);
9     end
```

```
1 function I = myreadimg(Folder, Num)
2     I = double(imread([Folder, sprintf('%08d', Num), '.jpg']))/255;
```

#### A.1.2 Background Estimation Functions

```
1 function [Out] = eraseRegion(Img, C, Size)
2     Out = Img;
3     %Find the pixels on the vertices of the bounding box
4     %surrounding the robot. top-t, bottom-b, left-l, right-r
5     t = max(1, C(1) - Size/2);
6     b = min(size(Img, 1), C(1) + Size/2);
7     l = max(1, C(2) - Size/2);
8     r = min(size(Img, 2), C(2) + Size/2);
9     %Find the average of the four pixels at the vertices of the
10    %bounding box
11    Avg = Img(t, l, :) + Img(t, r, :) + Img(b, l, :) + Img(b, r, :);
12    Avg = Avg / 4;
13    %Replace the image segment (I.e. the robot) with the average
14    %of the four pixels
15    for y = t:b
16        for x = l:r
17            Out(y, x, :) = Avg;
18        end
19    end
```

#### A.1.3 Detection Algorithm Helper Functions

```
1 function [ImgR, ImgG, ImgB] = processChannels(Img, FilterSize, FilterWidth)
2
3
4     % Blur the image
5     FImg = myimgblur(Img, FilterSize, FilterWidth);
6
7     % Normalise the image
8     NImg = normalize.rgb(FImg);
9
10    % Split the image into its three colour channels
11    ImgR = NImg(:,:,1);
12    ImgG = NImg(:,:,2);
```

```

13     ImgB = NIImg(:,:,3);
14
15     % Subtract the blue channel from the green channel
16     % to remove some of the excess blue in the green channel
17     ImgG = ImgG - 0.2 * ImgB;
18
19     % Renormalise each channel
20     ImgR = normchannel(ImgR);
21     ImgG = normchannel(ImgG);
22     ImgB = normchannel(ImgB);

```

```

1 function [Out] = myimgblur(Img, WindowSize, BlurWidth)
2     global HaveToolbox;
3     if HaveToolbox
4         Filter = fspecial('gaussian', [WindowSize WindowSize], BlurWidth);
5         Out = imfilter(Img, Filter, 'symmetric', 'conv');
6     else
7         % Correct between the width parameter of fspecial and the one of
8         % mygausswin :(
9         BlurWidth = WindowSize / BlurWidth;
10
11     Filter = mygausswin(WindowSize, BlurWidth) * mygausswin(WindowSize, BlurWidth)';
12     Filter = Filter / sum(reshape(Filter,1,numel(Filter)));
13
14     % crop the convolved image to original size
15     HalfWidth = floor(WindowSize/2);
16
17     MinX = HalfWidth + 1;
18     MaxX = size(Img, 2) + HalfWidth;
19
20     MinY = HalfWidth + 1;
21     MaxY = size(Img, 1) + HalfWidth;
22
23     Out = Img;
24     for i = 1:3
25         F = conv2(Img(:,:,:,i), Filter);
26         Out(:,:,:,i) = F(MinY:MaxY, MinX:MaxX);
27     end
28 end

```

```

1 function [OutImg] = normalize_rgb(Img)
2     OutImg = zeros(size(Img));
3     % SumImg = sum(Img, 3);
4     [H,W,C] = size(Img);
5     SumImg = zeros(H, W);
6     % ColW = [0.3 0.59 0.11] * 3;
7     ColW = [1.0 1.0 1.0];
8     for i = 1:3
9         SumImg = SumImg + Img(:,:,:,i) .* ColW(i);
10    end
11    SumImg = SumImg + (SumImg == 0);
12    for i = 1:3
13        OutImg(:,:,:,i) = Img(:,:,:,i) ./ SumImg;
14    end

```

```

1 function [Out] = normchannel(Img)
2     Pixels = reshape(Img, 1, numel(Img));
3     %Avg = mean(Pixels);
4     %Std = std(Pixels);
5     %Out = 0.1 * (Img - Avg) / Std;
6     Max = max(Pixels);
7     Min = min(Pixels);

```

```
8     Out = (Img - Min) / (Max - Min);
```

```

1 function [C, T] = xyhistmax(Img)
2 % find the maximum value along each axis
3 XHist = max(Img, [], 1)';
4 YHist = max(Img, [], 2);
5 % convolve it to get some smoothing
6 XHist = convhist(XHist, 20, 5);
7 YHist = convhist(YHist, 20, 5);
8
9 C = [0 0];
10 Max = [0 0];
11
12 % find the maximum along each axis
13 Max(1) = max(YHist);
14 Max(2) = max(XHist);
15
16 % find the range around this value where the axis max is within some
17 % threshold of the max
18
19 YExtent = find(YHist > 0.9 * Max(1));
20 XExtent = find(XHist > 0.9 * Max(2));
21 C(1) = round(mean(YExtent));
22 C(2) = round(mean(XExtent));
23 T = 0.75 * min(Max(1), Max(2));
24
25 % hFig = figure(2);
26 % clf();
27 % set(hFig, 'Position', [0 0 640 480]);
28 % axis([0, 640, 0, 1]);
29 % hold on;
30 % plot(XHist, 'r');
31 %
32 % line([0 640], [Max(2) Max(2)], 'Color', [0 0 0]);
33 % line([0 640], [0.9*Max(2) 0.9*Max(2)]);
34 % line([0 640], [T T], 'Color', [0 0 0]);
35 % line([C(2) C(2)], [0 0.9*Max(2)]);
36 % line([min(XExtent) min(XExtent)], [0 0.9*Max(2)]);
37 % line([max(XExtent) max(XExtent)], [0 0.9*Max(2)]);
38 % pause(3);
```

```

1 % find a threshold from a histogram by smoothing with a gaussian with
2 % standard deviation sigma and find the low valley location
3 % sizeparam should be at least 4, with larger giving less smoothing
4 function thresh = findthresh(thehist)
5
6 [len,x] = size(thehist);
7
8 tmp1=thehist;
9
10 % find largest peak
11 peak = find(tmp1 == max(tmp1));
12
13 % find highest peak to left
14 xmaxl = -1;
15 pkl = -1;
16 for i = 2 : peak-1
17     if tmp1(i-1) < tmp1(i) & tmp1(i) ≥ tmp1(i+1)
18         if tmp1(i) > xmaxl
19             xmaxl = tmp1(i);
20             pkl = i;
21         end
22     end
23 end
```

```

24     if pkl == -1
25         pkl = 1;
26         xmaxl = 1;
27     end
28 %      [pkl,xmaxl]
29
30 % find deepest valley between peaks
31 xminl = max(tmp1)+1;
32 vall = -1;
33 for i = pkl+1 : peak-1
34     if tmp1(i-1) > tmp1(i) & tmp1(i) ≤ tmp1(i+1)
35         if tmp1(i) < xminl
36             xminl = tmp1(i);
37             vall = i;
38         end
39     end
40 end
41 if vall == -1
42     vall = 2;
43     xminl = 2;
44 end
45 %      [vall,xminl]
46
47 % find highest peak to right
48 xmaxr = -1;
49 pkr = -1;
50 for i = peak+1 : len-1
51     if tmp1(i-1) < tmp1(i) & tmp1(i) ≥ tmp1(i+1)
52         if tmp1(i) > xmaxr
53             xmaxr = tmp1(i);
54             pkr = i;
55         end
56     end
57 end
58 if pkr == -1
59     pkr = len;
60     xmaxr = 1;
61 end
62 %      [pkr,xmaxr]
63
64 % find deepest valley between peaks
65 xminr = max(tmp1)+1;
66 valr = -1;
67 for i = peak+1 : pkr-1
68     if tmp1(i-1) > tmp1(i) & tmp1(i) ≤ tmp1(i+1)
69         if tmp1(i) < xminr
70             xminr = tmp1(i);
71             valr = i;
72         end
73     end
74 end
75 if valr == -1
76     valr = len-1;
77     xminr = 2;
78 end
79 %      [valr,xminr]
80
81 % find lowest point between peaks
82 if xmaxr > xmaxl
83     thresh = valr;
84 else
85     thresh = vall;
86 end
87
88 thresh = thresh-1;    % subtract 1 as histogram bin 1 is for value 0

```

```

1 function [Out] = cliprect(Img, Centre, Size)
2     YMin = round(max(1, Centre(1) - Size/2));
3     YMax = round(min(size(Img, 1), Centre(1) + Size/2));
4     XMin = round(max(1, Centre(2) - Size/2));
5     XMax = round(min(size(Img, 2), Centre(2) + Size/2));
6     Out = Img(YMin:YMax, XMin:XMax);
7 end

```

#### A.1.4 Linking Algorithm Functions

```

1 function [verticesX, verticesY, centroidX, falseImageX] = calcBoundingBox(TImgX)
2 global HaveToolbox;
3 %Set the image thresholds used to determine
4 %if the detected object is indeed a robot
5 thresholdUpper=4000;
6 thresholdLower=1500;
7 falseImageX=0;
8
9 %Label the image
10 [labelX, numXBlobs] = mybwlabel(TImgX);
11
12 %Initialise the centroid variable to hold the coordinates
13 %of the bounding box
14 centroidX = zeros(1,2);
15
16 %Then extract the various properties from the image
17
18 %if the image toolbox is available
19 if HaveToolbox==1
20 blobMeasurements = regionprops(labelX, ['basic']);
21 if size(blobMeasurements,1) == 0
22     verticesX = [0 0 0 0 0];
23     verticesY = [0 0 0 0 0];
24     centroidX = [0 0];
25     return;
26 end
27 end
28
29 %Calculate the area for each blob obtained from 'labelX'
30 allBlobAreas = [];
31 for i=1:numXBlobs
32     [rows,cols,vals] = find(labelX==i);
33     blobSize = sum(vals);
34     allBlobAreas = [allBlobAreas blobSize];
35
36 end
37
38 %Find the blob with the maximum area in the image
39 [maxBlobArea, index] = max(allBlobAreas);
40
41 %If there are no 'blobs' (objects) in the image
42 if numXBlobs == 0 || maxBlobArea==0
43     verticesX = [0 0 0 0 0];
44     verticesY = [0 0 0 0 0];
45     centroidX = [0 0];
46     return;
47 end
48
49
50 if HaveToolbox==1
51 %Extract the bounding box from the image toolbox
52 boundingBox = blobMeasurements(index).BoundingBox;
53 x1 = boundingBox(1);

```

```

54 y1 = boundingBox(2);
55 x2 = x1 + boundingBox(3) - 1;
56 y2 = y1 + boundingBox(4) - 1;
57 elseif HaveToolbox==0
58 %Without using the image toolkit, extract the bounding box
59 [rows,cols,vals] = find(labelX==index);
60 x1 = min(cols);
61 x2 = max(cols);
62 y1 = min(rows);
63 y2 = max(rows);
64 end
65 %determine the vertices of the bounding box
66 verticesX = [x1 x2 x2 x1 x1];
67 verticesY = [y1 y1 y2 y2 y1];
68 %Determine the centroid of the bounding box surrounding the robot
69 centroidX(1,1) = (x2+x1)/2;
70 centroidX(1,2) = (y2+y1)/2;
71
72 %*****
73 %Not fully implemented as it was found that this
74 %algorithm depends on the camera position
75
76 %Check the area of the blob to determine
77 %whether the blob falls within the correct region.
78 if(maxBlobArea> thresholdUpper || ...
79     maxBlobArea<thresholdLower)
80     %If the blob is greater than the predetermined
81     %threshold size of the robot, then the blob
82     %is probably not a robot
83     falseImageX= 1;
84 else
85     falseImageX=0;
86 end
87 %*****
88
89
90 end

```

```

1 function [centerMassX, centerMassY] = calcBoundingBoxCM(verticesX, verticesY, TImg)
2
3 %Initialise Area counter to determine how many pixels
4 %the robot in the image contains
5 areaCounter = 0;
6
7 %The center of mass coordinates for the robot are initialised
8 centerMassX = 0;
9 centerMassY = 0;
10
11 %Convert vertices of type double to integers
12 verticesX = round(verticesX);
13 verticesY = round(verticesY);
14
15 %Calculate the area of the object within the bounding Box
16
17 for x = verticesX(1):verticesX(2)
18     for y = verticesY(1):verticesY(3)
19         TImg(y,x);
20         if(TImg(y,x)==1)
21             areaCounter = areaCounter+1;
22         else
23             areaCounter;
24         end
25     end
26 end
27
28

```

```

29 %Calculate the center of mass for the image
30 centerMass=zeros(1,2);
31 for r=verticesX(1):verticesX(2)
32     for c=verticesY(1):verticesY(3)
33         centerMass(1,1) = centerMass(1,1)+r*TImg(c,r);
34         centerMass(1,2) = centerMass(1,2)+c*TImg(c,r);
35     end
36 end
37 %The x coordinate center of mass
38 centerMassX= centerMass(1,1)/areaCounter;
39 %The y coordinate center of mass
40 centerMassY= centerMass(1,2)/areaCounter;

```

### A.1.5 Orientation Algorithm Third Party Helper Function

```

1 %Retrieved from http://www.mathworks.com/matlabcentral/fileexchange/3345-plot-arrowhead
2 %Author: Ohad Gal
3 %Date of creation: 27 April 2003
4
5 function handles = plot_arrow( x1,y1,x2,y2,varargin )
6 %
7 % plot_arrow - plots an arrow to the current plot
8 %
9 % format: handles = plot_arrow( x1,y1,x2,y2 [,options...] )
10 %
11 % input: x1,y1 - starting point
12 %        x2,y2 - end point
13 %        options - come as pairs of "property","value" as defined for "line" and "patch"
14 %                  controls, see matlab help for listing of these properties.
15 %                  note that not all properties where added, one might add them at the end of this file
16 %
17 % additional options are:
18 % 'headwidth': relative to complete arrow size, default value is 0.07
19 % 'headheight': relative to complete arrow size, default value is 0.15
20 %                 (encoded are maximal values if pixels, for the case that the arrow is very long)
21 %
22 % output: handles - handles of the graphical elements building the arrow
23 %
24 % Example: plot_arrow( -1,-1,15,12,'linewidth',2,'color',[0.5 0.5 0.5],'facecolor',[0.5 0.5 0.5] );
25 %           plot_arrow( 0,0,5,4,'linewidth',2,'headwidth',0.25,'headheight',0.33 );
26 %           plot_arrow; % will launch demo
27
28 % =====
29 % for debug - demo - can be erased
30 % =====
31 if (nargin==0)
32     figure;
33     axis;
34     set( gca, 'nextplot', 'add' );
35     for x = 0:0.3:2*pi
36         color = [rand rand rand];
37         h = plot_arrow( 1,1,50+rand*cos(x),50+rand*sin(x),...
38             'color',color,'facecolor',color,'edgecolor',color );
39         set( h,'linewidth',2 );
40     end
41     hold off;
42     return
43 end
44 % =====
45 % end of for debug
46 % =====
47
48
49 % =====

```

```

50 % constants (can be edited)
51 %
52 alpha      = 0.15;    % head length
53 beta       = 0.07;    % head width
54 max_length = 22;
55 max_width  = 10;
56
57 %
58 % check if head properties are given
59 %
60 % if ratio is always fixed, this section can be removed!
61 if ~isempty( varargin )
62     for c = 1:floor(length(varargin)/2)
63         try
64             switch lower(varargin{c*2-1})
65                 % head properties - do nothing, since handled above already
66                 case 'headheight',alpha = max( min( varargin{c*2},1 ),0.01 );
67                 case 'headwidth', beta = max( min( varargin{c*2},1 ),0.01 );
68             end
69         catch
70             fprintf( 'unrecognized property or value for: %s\n',varargin{c*2-1} );
71         end
72     end
73 end
74
75 %
76 % calculate the arrow head coordinates
77 %
78 den      = x2 - x1 + eps;                                % make sure no devision by zero occurs
79 teta     = atan( (y2-y1)/den ) + pi*(x2<x1) - pi/2;   % angle of arrow
80 cs       = cos(teta);                                    % rotation matrix
81 ss       = sin(teta);
82 R        = [cs -ss;ss cs];
83 line_length = sqrt( (y2-y1)^2 + (x2-x1)^2 );          % sizes
84 head_length = min( line_length*alpha,max_length );
85 head_width  = min( line_length*beta,max_length );
86 x0        = x2*cs + y2*ss;                             % build head coordinates
87 y0        = -x2*ss + y2*cs;
88 coords    = R*[x0 x0+head_width/2 x0-head_width/2; y0 y0-head_length y0-head_length];
89
90 %
91 % plot arrow (= line + patch of a triangle)
92 %
93 h1        = plot( [x1,x2],[y1,y2], 'k' );
94 h2        = patch( coords(1,:),coords(2,:),[0 0 0] );
95
96 %
97 % return handles
98 %
99 handles = [h1 h2];
100
101 %
102 % check if styling is required
103 %
104 % if no styling, this section can be removed!
105 if ~isempty( varargin )
106     for c = 1:floor(length(varargin)/2)
107         try
108             switch lower(varargin{c*2-1})
109
110                 % only patch properties
111                 case 'edgecolor', set( h2,'EdgeColor',varargin{c*2} );
112                 case 'facecolor', set( h2,'FaceColor',varargin{c*2} );
113                 case 'facelighting',set( h2,'FaceLighting',varargin{c*2} );
114                 case 'edgelighting',set( h2,'EdgeLighting',varargin{c*2} );
115
116                 % only line properties

```

```

117         case 'color'      , set( h1,'Color',varargin{c*2} );
118
119         % shared properties
120         case 'linestyle', set( handles,'LineStyle',varargin{c*2} );
121         case 'linewidth', set( handles,'LineWidth',varargin{c*2} );
122         case 'parent'   , set( handles,'parent',varargin{c*2} );
123
124         % head properties - do nothing, since handled above already
125         case 'headwidth';
126         case 'headheight';
127
128     end
129
130     catch
131         fprintf( 'unrecognized property or value for: %s\n',varargin{c*2-1} );
132     end
133 end

```

### A.1.6 Main Program Code

```

1 % Clear any existing state
2 clear all;
3 clc;
4 clf;
5 tic
6
7 % Configuration section
8 DATA_FOLDER = 'data10/';
9 ENABLE_TOOLBOX = 1;
10 IMG_SKIP = 5;
11 IMG_STEP = 1;
12 MAX_IMG_COUNT = 100;
13 FILTER_SIZE = 5;
14 FILTER_WIDTH = 5;
15 BB_SIZE = 120;
16
17 % Attempt to acquire a toolbox license
18 global HaveToolbox;
19 HaveToolbox = ENABLE_TOOLBOX && license('checkout', 'Image_Toolbox');
20
21 % Load in the dataset
22 ImgData = myreadfolder(DATA_FOLDER, MAX_IMG_COUNT);
23
24 % Compute the median image
25 MedianIndices = [5 85 95];
26 MedianImgs = zeros(size(ImgData,1), ...
27                      size(ImgData,2), ...
28                      size(ImgData,3), ...
29                      size(MedianIndices, 2), ...
30                      class(ImgData));
31
32
33 for Idx = 1:size(MedianIndices,2)
34     ImgIdx = MedianIndices(Idx);
35
36     Img = ImgData(:,:,:,:ImgIdx);
37
38     [ImgR, ImgG, ImgB] = processChannels(Img, FILTER_SIZE, FILTER_WIDTH);
39
40     % Marginal Histogram along X-axis, Y-axis
41     [CR, ThreshR] = xyhistmax(ImgR);
42     [CG, ThreshG] = xyhistmax(ImgG);
43     [CB, ThreshB] = xyhistmax(ImgB);
44

```

```

45     Img = eraseRegion(Img, CR, BB_SIZE);
46     Img = eraseRegion(Img, CG, BB_SIZE);
47     Img = eraseRegion(Img, CB, BB_SIZE);
48
49     MedianImgs(:,:,:,:Idx) = Img;
50 end
51
52 MedImg = median(MedianImgs, 4);
53
54 OldDirR = [0 0];
55 OldDirG = [0 0];
56 OldDirB = [0 0];
57
58 %*****
59 %The variables used to link the objects movement
60
61 XLinkerR = [];
62 YLinkerR = [];
63 XLinkerG = [];
64 YLinkerG = [];
65 XLinkerB = [];
66 YLinkerB = [];
67
68 MissCount = 0;
69
70 for ImgIdx = IMG_SKIP:IMG_STEP:MAX_IMG_COUNT
71     Img = ImgData(:,:,:,:ImgIdx);
72
73     [ImgR, ImgG, ImgB] = processChannels(Img, FILTER_SIZE, FILTER_WIDTH);
74
75     % Marginal Histogram along X-axis, Y-axis
76     [CR, ThreshR] = xyhistmax(ImgR);
77     [CG, ThreshG] = xyhistmax(ImgG);
78     [CB, ThreshB] = xyhistmax(ImgB);
79
80     TImgR = cliprect(ImgR, CR, BB_SIZE)>ThreshR;
81     TImgG = cliprect(ImgG, CG, BB_SIZE)>ThreshG;
82     TImgB = cliprect(ImgB, CB, BB_SIZE)>ThreshB;
83
84     %*****
85     %Calculate and display the bounding box for the image
86     %Relative to the clipped image from the cliprect function
87     [VerticesXR, VerticesYR, CentroidR, FalseImageR] = calcBoundingBox(TImgR);
88     [VerticesXG, VerticesYG, CentroidG, FalseImageG] = calcBoundingBox(TImgG);
89     [VerticesXB, VerticesYB, CentroidB, FalseImageB] = calcBoundingBox(TImgB);
90
91     %*****
92     %If no image is detected, skip the current frame
93     if min(VerticesXR) == 0 || min(VerticesXG) == 0 || min(VerticesXB) == 0
94         MissCount = MissCount + 1;
95         continue;
96     end
97     %Calculate the center of mass of the robot within a
98     %bounding box
99     [CenterMassXR,CenterMassYR] = calcBoundingBoxCM(VerticesXR, VerticesYR, TImgR);
100    [CenterMassXG,CenterMassYG] = calcBoundingBoxCM(VerticesXG, VerticesYG, TImgG);
101    [CenterMassXB,CenterMassYB] = calcBoundingBoxCM(VerticesXB, VerticesYB, TImgB);
102
103    %Add variables for the center of mass of the
104    %robot relative to the original image
105    trueCMR = (CenterMassXR + CR(2) - size(TImgR, 2)/2);
106    trueCMYR = (CenterMassYR + CR(1) - size(TImgR, 1)/2);
107    trueCMXG = (CenterMassXG + CG(2) - size(TImgG, 2)/2);
108    trueCMYG = (CenterMassYG + CG(1) - size(TImgG, 1)/2);
109    trueCMXB = (CenterMassXB + CB(2) - size(TImgB, 2)/2);
110    trueCMYB = (CenterMassYB + CB(1) - size(TImgB, 1)/2);
111
```

```

112 %Store the true position of the bounding box centroid
113 %relative to the coordinates of the original image
114 trueCentroidBBXR = (CentroidR(1) + CR(2) - size(TImgR, 2)/2);
115 trueCentroidBBYR = (CentroidR(2) + CR(1) - size(TImgR, 1)/2);
116 trueCentroidBBXG = (CentroidG(1) + CG(2) - size(TImgG, 2)/2);
117 trueCentroidBBYG = (CentroidG(2) + CG(1) - size(TImgG, 1)/2);
118 trueCentroidBBXB = (CentroidB(1) + CB(2) - size(TImgB, 2)/2);
119 trueCentroidBBYB = (CentroidB(2) + CB(1) - size(TImgB, 1)/2);
120
121 %*****%
122 %To link tracks on the estimated background image
123 XLinkerR = [XLinkerR trueCMXR];
124 YLinkerR = [YLinkerR trueCMYR];
125 XLinkerG = [XLinkerG trueCMXG];
126 YLinkerG = [YLinkerG trueCMYG];
127 XLinkerB = [XLinkerB trueCMXB];
128 YLinkerB = [YLinkerB trueCMYB];
129
130 %Define unit vectors in the direction of the bounding
131 %box centroid for each of the rgb channels respectively
132 CenterMassR = [CenterMassXR CenterMassYR];
133 DR = (CentroidR - CenterMassR);
134
135 CenterMassG = [CenterMassXG CenterMassYG];
136 DG = (CentroidG - CenterMassG);
137
138 CenterMassB = [CenterMassXB CenterMassYB];
139 DB = (CentroidB - CenterMassB);
140
141 %Calculate the unit vectors for each channel
142 DR = DR/norm(DR);
143 DG = DG/norm(DG);
144 DB = DB/norm(DB);
145
146 %Colour for the orientation arrows in the bouding box
147 LineColR = 'b-';
148 LineColG = 'b-';
149 LineColB = 'b-';
150
151 %Colour for the orientation arrows on the main image
152 LineColRArrow = [0 0 1];
153 LineColGArrow = [0 0 1];
154 LineColBArrow = [0 0 1];
155 %Calculate the dot product between the arrows current
156 %orientation and its previous orientation. If the value
157 %is less than 0.5, then the arrow is pointing in an incorrect
158 %direction
159 if dot(DR, OldDirR) < 0.5
160 %Arrow is pointing in an incorrect direction,
161 %therefore make the arrow red to indicate this.
162 LineColR = 'r-';
163 LineColRArrow = [1 0 0];
164 end
165 if dot(DG, OldDirG) < 0.5
166 LineColG = 'r-';
167 LineColGArrow = [1 0 0];
168 end
169 if dot(DB, OldDirB) < 0.5
170 LineColB = 'r-';
171 LineColBArrow = [1 0 0];
172 end
173 OldDirR = DR;
174 OldDirG = DG;
175 OldDirB = DB;
176
177 figure(1);
178 clf();

```

```

179 %*****
180 %Plotting the main images
181
182 subplot(3,3,1:6);
183 %myimshow(MedImg);
184 myimshow(Img);
185 hold on
186 plot(XLinkerR, YLinkerR, 'xr-', XLinkerG, YLinkerG, 'xg-', XLinkerB, YLinkerB, 'xb-');
187 xlabel(ImgIdx);
188 myimshow(Img);
189 colormap('default');
190 hold on;
191 %Plot the arrow on each of the cars to indicate their
192 %orientation
193 plot_arrow(trueCMXR,trueCMYR, trueCentroidBBXR+30*DR(1),trueCentroidBBYR+30*DR(2),...
194 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColRArrow, ...
195 'facecolor',LineColRArrow);
196 hold on
197 plot_arrow(trueCMXG,trueCMYG, trueCentroidBBXG+30*D(1),trueCentroidBBYG+30*D(2),...
198 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColGArrow, ...
199 'facecolor',LineColGArrow);
200 hold on
201 plot_arrow(trueCMXB,trueCMYB, trueCentroidBBXB+30*DB(1),trueCentroidBBYB+30*DB(2),...
202 'linewidth',2,'headwidth',0.25,'headheight',0.33,'color',LineColBArrow, ...
203 'facecolor',LineColBArrow);
204
205 %Plot the red channel with its corresponding bounding
206 %box
207 subplot(3,3,7);
208 myimshow(TImgR);
209 colormap('gray');
210 hold on;
211 plot(VerticesXR, VerticesYR, 'r-', 'LineWidth', 5);
212 plot_arrow(CenterMassR(1),CenterMassR(2), CentroidR(1)+30*DR(1),...
213 CentroidR(2)+30*DR(2), 'linewidth',2,'headwidth',0.25,'headheight',0.33,... ...
214 'color',LineColRArrow,'facecolor',LineColRArrow);
215 xlabel('Red Channel');
216
217 %Plot the green channel with its corresponding bounding
218 %box
219 subplot(3,3,8);
220 myimshow(TImgG);
221 colormap('gray');
222 hold on;
223 plot(VerticesXG, VerticesYG, 'g-', 'LineWidth', 5);
224 plot_arrow(CenterMassG(1),CenterMassG(2), CentroidG(1)+30*D(1),...
225 CentroidG(2)+30*D(2), 'linewidth',2,'headwidth',0.25,'headheight',0.33,... ...
226 'color',LineColRArrow,'facecolor',LineColRArrow);
227 xlabel('Green Channel');
228
229 %Plot the blue channel with its corresponding bounding
230 %box
231 subplot(3,3,9);
232 myimshow(TImgB);
233 colormap('gray');
234 hold on;
235 plot(VerticesXB, VerticesYB, 'b-', 'LineWidth', 5);
236 plot_arrow(CenterMassB(1),CenterMassB(2), CentroidB(1)+30*DB(1),...
237 CentroidB(2)+30*DB(2), 'linewidth',2,'headwidth',0.25,'headheight',0.33,... ...
238 'color',LineColBArrow,'facecolor',LineColBArrow);
239 xlabel('Blue Channel');
240 %*****
241 %pause(0.1);
242 input('...');
243 end
244 %*****
245 %Once the algorithm is finished, plot the background

```

```
246 %image with the linked tracks
247 clf();
248 myimshow(MedImg);
249 hold on
250 plot(XLinkerR, YLinkerR, 'xr-', XLinkerG, YLinkerG, 'xg-', XLinkerB, YLinkerB, 'xb-');
251 xlabel(ImgIdx);
252 input(int2str(MissCount));
253 toc
```