Eye Tracking
SIGB Spring 2014

Marcus Gregersen
mabg@itu.dk

Martin Faartoft
mlfa@itu.dk

Mads Westi
mwek@itu.dk

TODO DATO

1 Introduction

2 Pupil Detection

In this section, we will investigate and compare different techniques for pupil detection.

2.1 Thresholding

An obvious first choice of technique, is using a simple threshold to find the pupil, then do connected component (blob) analysis, and finally fit an ellipse on the most promising blobs.

Fig 1 shows an example of an image from the 'eye1.avi' sequence and the binary image produced by, using a threshold that blacks out all pixels with intensities above 93. This manages to separate the pupil nicely from the iris.

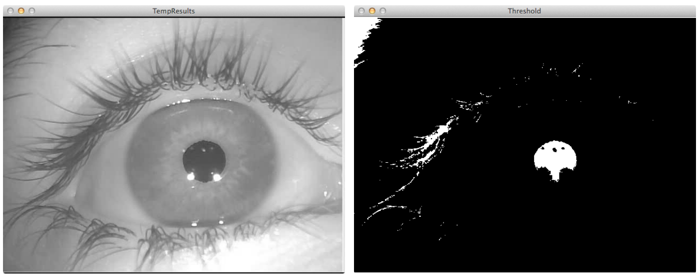


Figure 1: Thresholding eye1.avi

The next step, is to do connected component analysis, and fit an ellipsis through the blobs. As seen in fig 2, this succesfully detects the pupil, but is extremely prone to false positives.

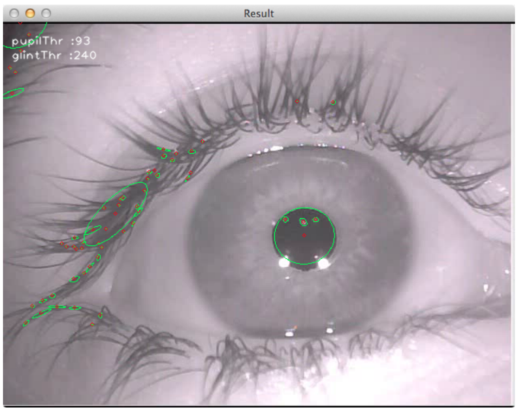


Figure 2: Fitting ellipses on blobs from eye1.avi (green figures are ellipses fitted through blobs, red dots are the centerpoint of each blob)

By experimenting, we find that requiring that the area of the blob lies in the interval [1000 : 10000], and the extent between [0.4 : 1.0], we eliminate most false positives on the entire eye1 sequence, while still keeping the true positive.

This approach has several problems, however. Note how the true positive on fig 2 fails to follow the bottom of pupil correctly. This is due to the glints obscuring part of the boundary between pupil and iris. It also makes some sweeping assumptions:

The pupil has size at least size 1000 If the person on the sequence leans back slightly, the pupil will shrink and we will fail to detect it.

A threshold of 93 will cleanly separate pupil from iris This is true for eye1.avi, but generalizes extremely poorly to the other sequences. If this approach is to be used across multiple sequences recorded in different lighting conditions, the threshold will have to be adjusted by hand for each one.

This problem can be mitigated somewhat with Histogram Equalization. A threshold of 25 on Histogram Equalized images, fares considerably better across several sequences. Note that this will still fail, if parts of the image are significantly darker than the pupil, thereby messing up the equalization.

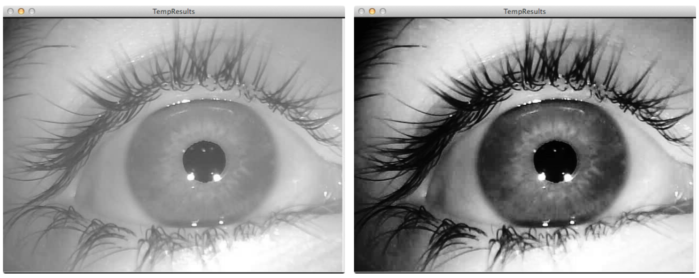


Figure 3: Eye1 before and after Histogram Equalization

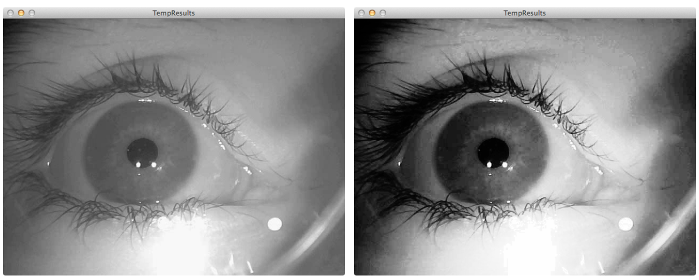


Figure 4: Eye3 before and after Histogram Equalization

Morphology Using Morphology, we can improve the detected pupil. The problem with the glints obscuring part of the boundary can be mitigated with the 'closing' operator - used to fill in holes in binary images. Fig 5 shows binary images before and after applying the closing operator. Notice how the noise inside the pupil is completely removed, and the glints are mostly removed. A downside to using the closing operation, is that adjacent, sparse structures may merge and resemble circles.

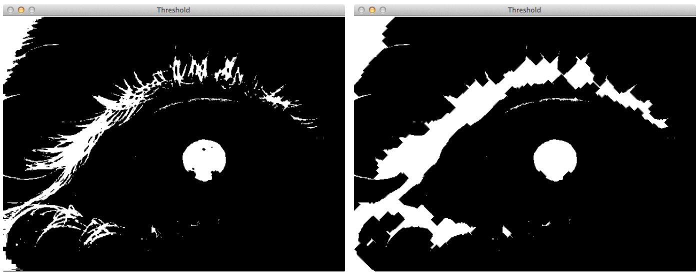


Figure 5: Eye1 before and after Closing (5 iterations, 5x5 CROSS structuring element)

Tracking The pupil tracker can be further improved, by using information about the pupil positions from the previous frame. We do it as follows:

1. Search within some threshold distance from each pupil in previous frame

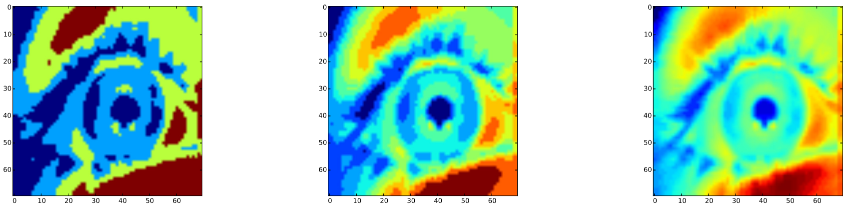
2. One or more pupils were found within the distance, return those

3. No pupils were found within the distance, search the entire image

Because of the fallback clause in '3', it is very unlikely that the true positive is not detected in each frame. The only case I can think of where this approach fails, is if the pupil is obscured for a frame (subject blinking for example), while a false positive is still detected. In that case, the pupil will improperly detected for as long as the false positive continues to be present.

2.2 Pupil Detection using k-means

An alternative method of pupil detection is by k-means clustering. The method separates the picture in K clusters. Each cluster is a set of pixels with values closer to the value of the cluster center, than the value of other cluster centres - cluster centres correspond to mean value of the cluster. The value of K is arbitrarily chosen, so that for a sufficiently large number of K the pupil is evaluated as a single separate cluster. If the pupil is a single cluster a binary image can easily be created and BLOB detection would only need to look at the one object. The following figure illustrates how different values of K impacts the segmentation.



(a) $K = 4$ (b) $K = 10$ (c) $K = 80$

Figure 6: K-kmeans for different values of K

For performance reasons, k-mean can not be calculated from the original image, the clustering is therefore done on a resized 70x70 pixel image. To reduce the impact of noise, the resized image is filtered with a gaussian filter. It is clear in figure 6 that even for a very high K, the pupil is not a separate cluster, Experiments has revealed that at a K value in the range of 10 to 20 yields something

Kmeans could also be used calculate a dynamic threshold value

The use use of k-means did not give a better result than order nary thresholding.

2.3 Pupil Detection using Gradient Magnitude

So far, we have been looking at the intensity values of the image. This has yielded reasonable approximate results, but is not as robust as we would like. In the following, we investigate what happens if we look at the change in intensity (the image gradient / first derivative), instead of the absolute intensity value at a given point. The gradients in the X and Y directions, are easily calculated with a Sobel filter. And from these, we can calculate the Gradient Magnitude as: $\sqrt{x^2 + y^2}$ (the Euclidean length of the vector x + y), and the orientation as: $arctan2(y, x)$. Fig 7 shows a subsampled cutout of the Gradient image of Eye1, featuring the pupil and glints.

Note that the pupil boundary is clearly visible on fig 7. We will attempt to use this information as follows: given an approximate centerpoint and radius for the pupil, scan in a number of directions, d from the centerpoint, find the location of the maximum gradient magnitudes along the line-segments that are described by the centerpoint, a direction from d and the radius. Use this set of points to fit an ellipse, and use that as improved pupil detection.

Figure 8(left) shows the lines considered, and the max gradient points found. Figure 8(right) shows the old and new pupil detections. This approach suffers the same problem as earlier. When the glints obscure part of the boundary, the pupil detection fails to follow the lower boundary. On top of that, there are also issues with noise, notice the red dots inside the top part of the pupil on fig 8, these are caused by non-system light reflecting off

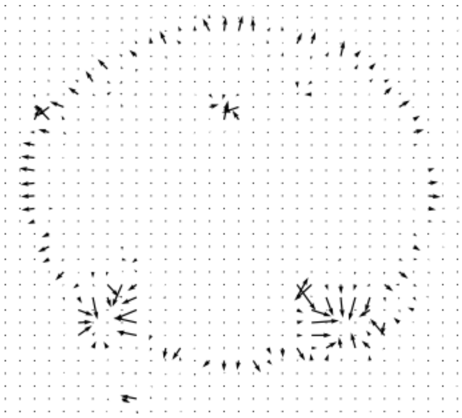


Figure 7: Quiver plot of Eye1 gradients (zoomed on pupil area)

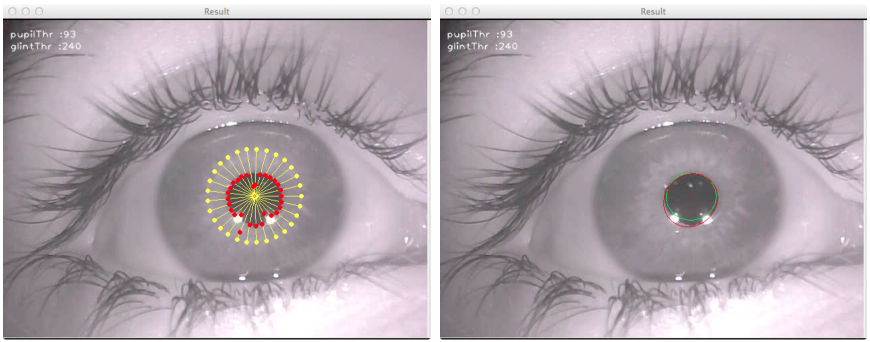


Figure 8: Left: Eye1 showing line-segments for gradient magnitude maximization (yellow) and maximum gradient values along the lines (red). Right: Eye1 showing pupil approximation (green), and new pupil detection (red)

the pupil.

The noise issues can be drastically reduced with proper pre-processing. Fig 9 shows much improved results, when blurring the image beforehand.

We experimented with ignoring gradient points where the orientation was too far from the orientation of the circle normal, but did not see any improvements to the pupil detection.

2.4 Pupil Detection by circular Hough transformation

In an attempt to make our pupil detection more robust we now investigate the result of applying a circular hough transformation on the eye images.

The main challenge is finding the correct parameters for the process. We consider the following parameters:

Gauss kernel size The size of the gaussian kernel that is applied to the image before the hough transformation

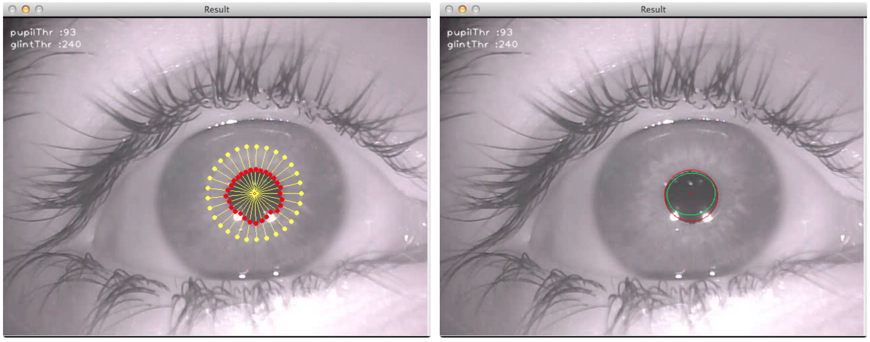


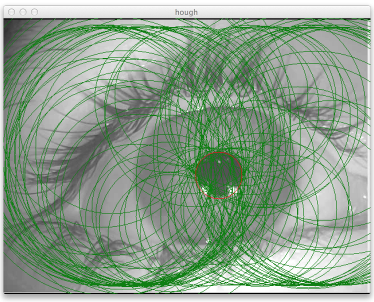
Figure 9: as fig 8, but pre-processed with a 9x9 Gaussian Blur

σ - value the standard deviation value used to construct the gaussian kernel.

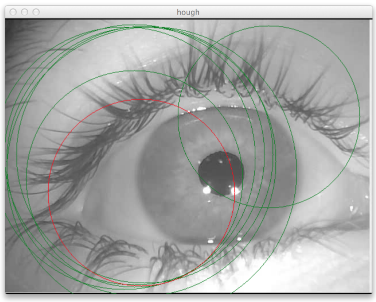
Accumulator threshold The minimum cummulative vote thresshold in which some parameters for a circle are considered.

Minimum and Maxiumum Radius The minumum and maximum radius of circles to consider.

The next step is to experimentally find the parameters that yields the best result over all sequences.

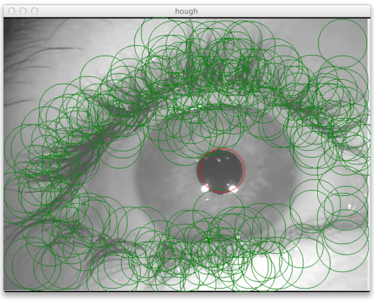


(a) Accumulator threshold at 100

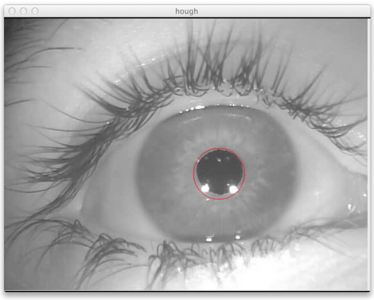


(b) Accumulator threshold at 150

Figure 10: Finding the accumulator threshold values



(a) Size=9, $\sigma = 9$



(b) Size=31, $\sigma = 9$

Figure 11: Preprocessing by smothing with a gaussian kernel

Discussion The circular hough transformation yields the most robust pupil detection we have been able to produce so far.

The intuition behind this is that in an ideal setting, where the eye for example is not distorted by perspective, the pupil is going to be near-circular, so the process of hough tranforming and then voting for circles is likely to succeed.

In a non ideal setting, for example in a frame were the eye is seen from the side the pupil is not going to yield the same circular properties, and the process is going to fail.

By preprocessing the image by smooting some of the noise is going to be filtered out. The idea is to choose a kernel that is rougly of the same size as the pupil. In this manner smaller features, such as eye lashes will be smothed away, but still maintaining the pupil feature.

The drawback of setting a constant size for the gaussian kernel is that is is not scale independent. An ideal kernel in some frame may smooth away the pupil in some other frame is the subject moved closer or futher away from the camera.

3 Glint Detection

4 Eye Corner Detection

5 Iris / Limbus Detection

6 Conclusion

References

[1] Foo

Appendix