Eye Gaze Tracking using Eigen-eyes and Support Vector Machines

Mohammed Shoaib and Shreshth Singhal

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Abstract

Human eye gaze tracking is an important problem with great potential in HCI. We created a robust but slow eye tracker using correlation-based techniques. We then built gaze-tracking mechanisms on top of this. Our approach to detect gaze direction was two-pronged: one using principal component analysis ('Eigen-eyes') and one using support vector machines. The accuracy of these methods was measured to peak around 60-62%.

1 Introduction

Eye gaze tracking means detecting the direction of line-of-sight of a person. Effective tracking of a person's gaze allows us to find out where their attention is focused. This valuable information can be leveraged in many ways. It can lead to new and potentially powerful human-computer interfaces, not only in theoretical systems and research, but in consumer applications. For example, a person could control the mouse on their computer using their gaze, allowing for quicker and more natural interaction. Consumer appliances like TVs could be equipped with simple cameras to perform basic tasks like turning on or changing a channel based on a person's gaze. There have been forays in using gaze-tracking in museums to display information about the objects that the person is looking at[3]. The application which motivated this project was that of using a person's gaze as a cue to scroll through documents while reading them (when the user reaches the end of a page, the document auto-scrolls to the next page).

There are of course, intrusive, active methods of detecting eye gaze. One can easily attach probes around a person's eye to detect motion and derive the gaze from this - in fact this was a common method in earlier gaze trackers[6]. There are also active methods which project infrared or near-infrared light onto the scene and detect the light reflected from the user's pupil as a bright spot. The line-of-sight can then be gauged from this[1][2].

We feel, for such a tracker to be a viable option in consumer applications, the goal must be to create a robust, non-invasive gaze tracker that works using simple cameras without needing any other active assistance. There has been considerable research into developing such schemes. A very interesting method exploits another vision problem - that of detecting head pose cues. This scheme uses a hybrid mechanism whereby the head pose and gaze are tracked independently using relatively weak trackers, and are then used mutually reinforce each other on successive iterations of the trackers[4]. Another very robust method is that of pupil center corneal reflection (PCCR). This method uses the 'glint' that appears on the cornea when a video is taken of the eye under sufficient light[7]. The naive PCCR method has its drawbacks though, most notably its poor performance under significant head movement. To allow for this, there is also a PCCR hybrid that allows for dynamic head movement compensation and works more robustly[8].

2 Goals and Challenges

Our goals in this project were more modest than creating a robust eye-gaze tracker that works perfectly even with considerable head movement. Our end goal was to design a system that would detect the direction of a person's gaze with decent accuracy. However, before tackling the eye gaze problem, we need to deal with tracking the eye. We need a method that can segment out the eye in a given set of video frames. Once we have the segmented eye, we need to extract the gaze information from it.

There are numerous challenges that occur simply because of the way the problem is formulated. Chief amongst these is the problem of dealing with head movement. This can be dealt with in the earlier eye tracking step more easily since it is relatively easy to segment out the eye as long as it is visible in the video. However, if we do this, then in the later stage, when we are trying to find the gaze direction, we have no information about the depth and orientation of the eye with respect to the camera. This limits our gaze tracking algorithms to those that work independent of knowledge about the eye's position. We can only use the image of the eye and how the pupil is displaced. Intuitively, from the perspective of human vision, this information is enough to figure out a person's line-of-sight. In fact, this is all the information that humans use to tell where a person is looking. Alternatively, if we wish to use the extra positional information, we can use more complicated mechanisms to allow for head movement as seen in [8].

Another issue that arises is that of lighting - what if the image of the eye isn't bright enough to glean any information from? Unfortunately, this can only be dealt with by artificially increasing the light in the scene.

3 Eye tracking

The first step is to acquire frames from the video capture device separated by an appropriate amount of time. The time lag between frames mainly depends on the application. The time lag should be enough that we don't get swamped with too much redundant image data. On the other hand, the frames need to be close together in time so that we don't end up missing any visual cues that the application may depend on (such as blinks or visual gestures). In our algorithm, there is an initial calibration step where the user must crop out the portion of any single frame that corresponds to their eye(s). This cropped out eye serves as a template for the eye segmentation algorithm.

For all the video frames, we compute the correlation coefficients between the template and all possible bounding boxes of the size of the template in the frame. The bounding box that gives the maximum correlation is the region where the eye is most likely to be. If the correlation coefficient at this point has a value greater than a suitably chosen threshold value, we can assume with some confidence that it is indeed the eye in that frame. Note that this threshold should be large enough to not allow false positives. On the other hand, it should not be so high that it doesn't allow for the expected variation in the way the eye looks from frame to frame.

4 Gaze tracking

Once we have acquired the images of the eye from all the required video frames, we need to extract information about the gaze in each of them. At this point, as we mentioned before, we have no positional information about the camera and the eye. All we have are the images of the eye themselves. To extract something useful out of these images, we need to compare them with 'canonical' images of the eye pointing in known directions. We can then compare our test images with these known images to figure out gaze direction. The term term 'compare' is somewhat loosely defined here. We will see further on what techniques are actually used to do this.

Note that this method limits us to only a fixed number of possible gaze directions, i.e. we have to quantize the space of gaze directions down to a bounded set that we can reasonably train our algorithm on. We have chosen 9 possible gaze directions in our implementation. Also, note that the calibration images will be most effective if they are of the user's eyes; however, if we subtract colour information, any person's eye will work relatively well.

With the test images and the training images that we have now, we use one of two techniques to find their correlation:

4.1 Eigen-eyes

Once we have the training images and the images of the eye from video, we can use singular value decomposition (SVD) and principal components analysis (PCA) in a variant of the well-known eigen-faces algorithm. First off, we compute the average eye image and subtract it out from all the training images. We then perform SVD on these normalized images to get the principal components of variation of the eye. We can also compute the weights of these training images relative to their principal components (i.e. the projections onto principal component axes).

Similarly, we normalize the test images from video, relative to the average eye. We then compute their weights relative to the principal components (similar to above). Now, given the weights of all test and training images relative to principal components, we can find the best match of each test image from all the given training images. Our algorithm simply computes the euclidean difference between the two weights. The training image that minimizes this distance for a given test image is said to be the closest match for that test image.

We know the direction of gaze of the eye in the best match training image. We can assume that the eye in the corresponding test image is also pointed in that direction.

4.2 Support Vector Machines

An alternative method for gaze tracking is using the SVM recognition technique. SVM is a basic recognition and classification technique that, at its simplest, is use to classify data into one of two classes, after being appropriately trained by examples of both classes. Theoretically, it achieves this by finding the hyperplane that separates the points corresponding to members of the two classes in a way that maximizes the margin between the hyperplane and members of the two sets. This problem reduces to a minimization problem subject to constraints of correctly classifying the data. From this programming problem, we learn the support vectors (that lie on the margin around the hyperplane). The hyperplane may sometimes need to be in a higher-dimension to correctly classify all data points. To avoid the transformation to higher dimensions, we can use kernel functions. These are nonlinear boundaries that work similar to how a linear boundary would in higher dimensions.

While the basic form of SVM is a binary classifier, it can be expanded by two different methods to become a multi-class classifier. The first, called 'one against all' trains by learning a binary SVM for one class versus a class that is the union of all the others. It classifies test data by applying such an SVM for each class. The class that returns the best matching value is the one that is deemed correct. The second method, called 'one against one' trains by learning an SVM for each pair of classes. To classify test data, we apply all these SVMs. The class that the test data is classified into the most is considered to be the correct class.

In our algorithm, we used a third-party SVM toolbox [5] to perform multi-class classification amongst our gaze classes.

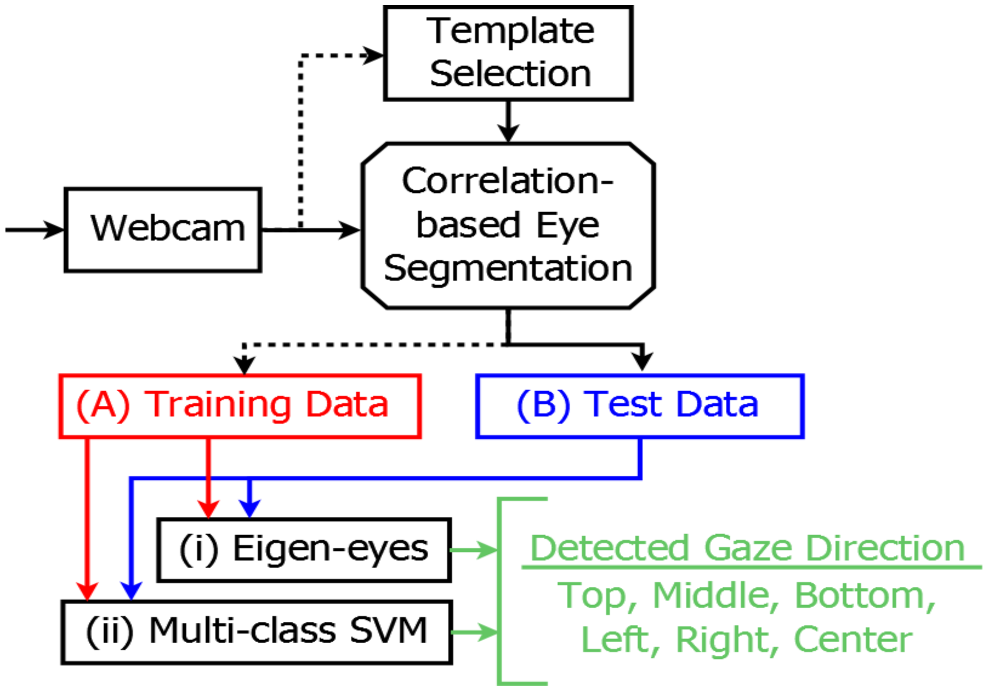
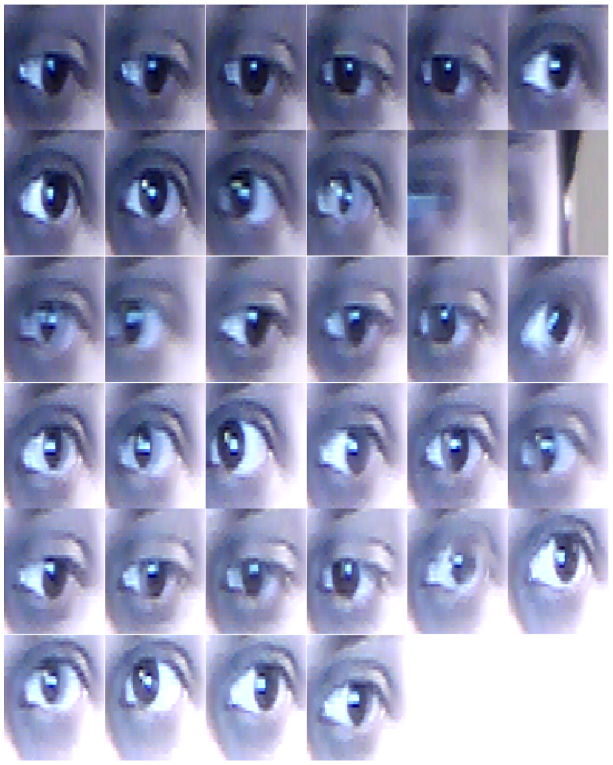


Figure 1: Flow-chart of the algorithm. Dashed lines are one-time training steps. Solid lines are continuous stream of data

5 Results

5.1 Eye tracking

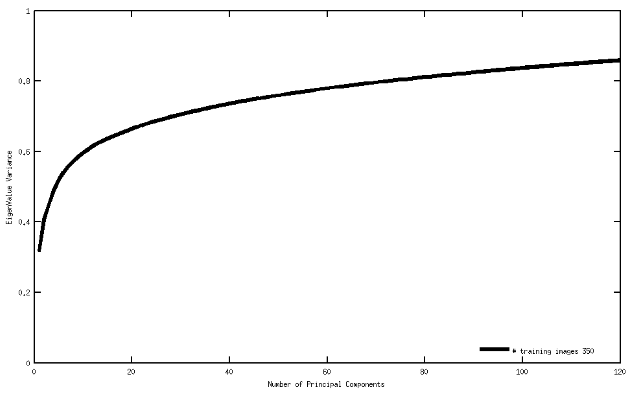


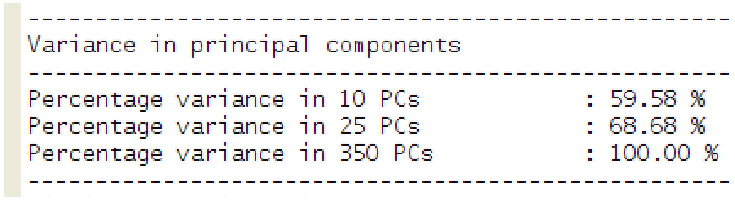
captionFigure 2: Results of eye segmentation

The above image shows the result of the eye segmentation algorithm for a general trial run. The user in front of the camera moved his eyes all around the screen. After picking the template, the bounding boxes in all the frames are correlated to find the best match with the eye. As can be seen in this, the algorithm does quite a good job. In all but one frame (plus another hazy frame), the correct eye position has been found; in fact the bounding box is found such that the eye is centered in most of these images. This provides a fairly uniform dataset for the gaze tracker to work with.

The cons of this approach is that the segmentation step is quite slow. It can take a upto 2 minutes or so to segment the eye from 50 test frames. Also, if the user picks a larger template, then we end up with more information than necessary. In fact, in the gaze tracking step, if there is too much information outside the eye itself, it can be detrimental as it reduces the importance of the eye and the direction where the eye is pointing. This can lead to a lot of false positives in gaze tracking, since images will be matched to the wrong set.

5.2 Eigen-eyes





```
---------------------------------------------------------
Variance in principal components
---------------------------------------------------------
Percentage variance in 10 PCs                : 59.58 %
Percentage variance in 25 PCs                : 68.68 %
Percentage variance in 350 PCs               : 100.00 %
---------------------------------------------------------
```

Figure 3: Variance in eigenvalues as a function of number of principal components (units on the X-axis are in increments of 20).

When using the Eigen-eyes algorithm, we can see that the variation in the eigenvalues plateaus after 15-20 distinct principal components are chosen. The number of principal components chosen to run the algorithm is an important consideration. More principal components mean we get more precise reconstruction and matching of the test images; however, this comes at the cost of extra computation. As we can see from the above graph, the law of diminishing returns applies and we don't get much added benefit in going beyond 20 eigen-eyes.

When using 25 eigen-eyes, we get the follow- ing results:

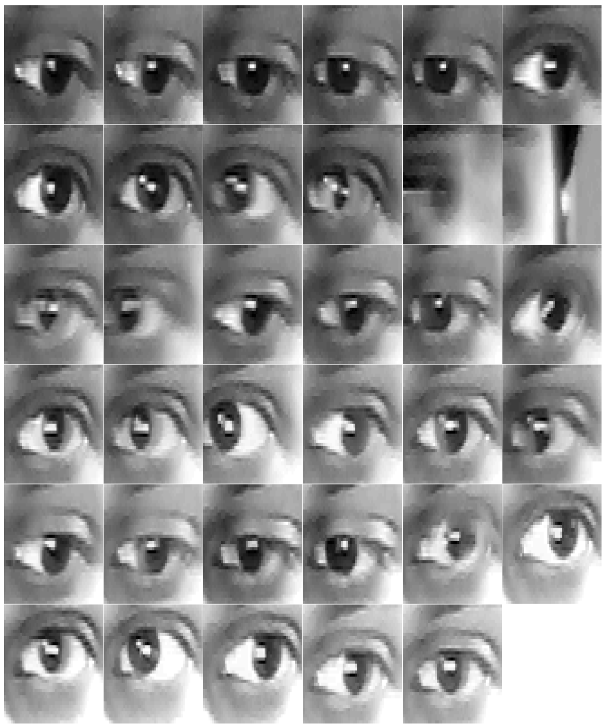


Figure 4: Test images

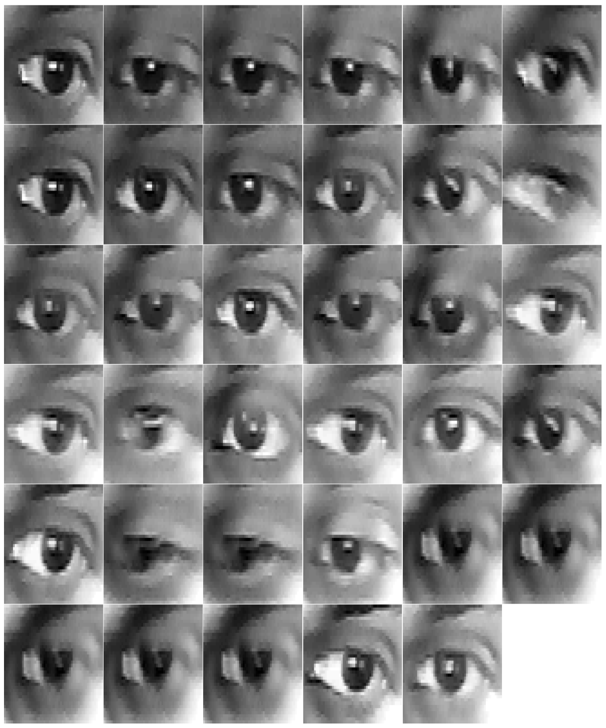
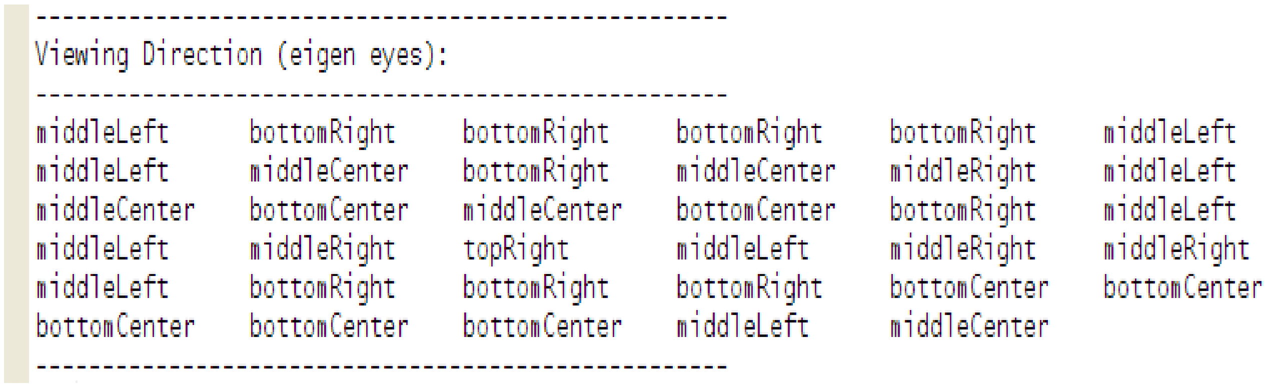


Figure 5: Corresponding best-match training images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Viewing Direction (eigen eyes):
---------------------------------------------------
middleLeft      bottomRight     bottomRight     bottomRight     bottomRight     middleLeft
middleLeft      middleCenter    bottomRight     middleCenter    middleRight     middleLeft
middleCenter    bottomCenter    middleCenter    bottomCenter    bottomRight     middleLeft
middleLeft      middleRight     topRight        middleLeft      middleRight     middleRight
middleLeft      bottomRight     bottomRight     bottomRight     bottomCenter    bottomCenter
bottomCenter    bottomCenter    bottomCenter    middleLeft      middleCenter
---------------------------------------------------
```

Figure 6: Corresponding best-match gaze direction

This gives 21 correct out of 35, a success rate of 60%.

Using 15 eigenvalues instead, we get the following:

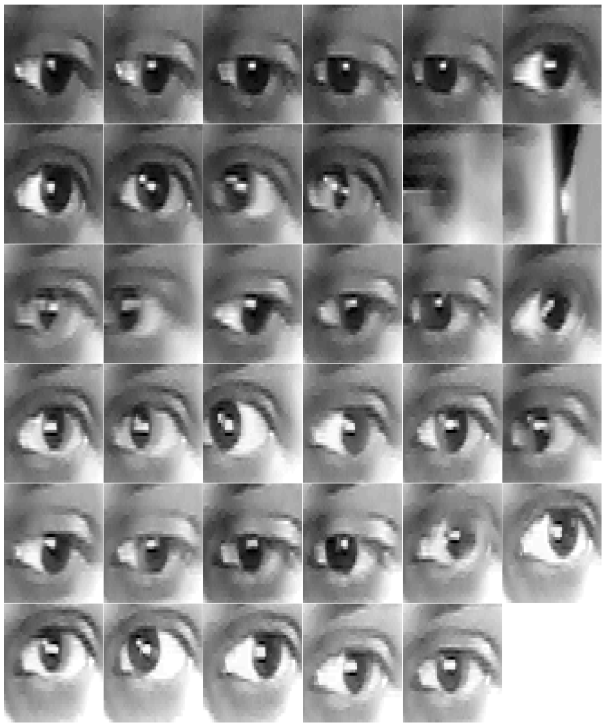


Figure 7: Test images

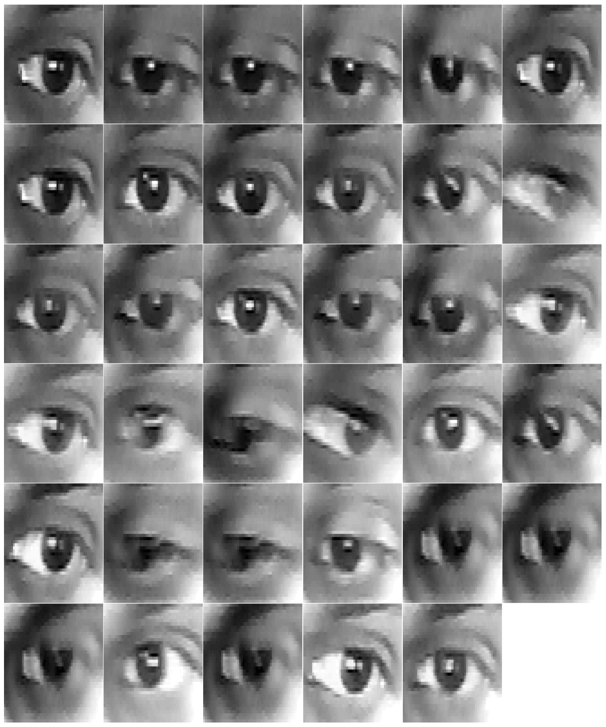
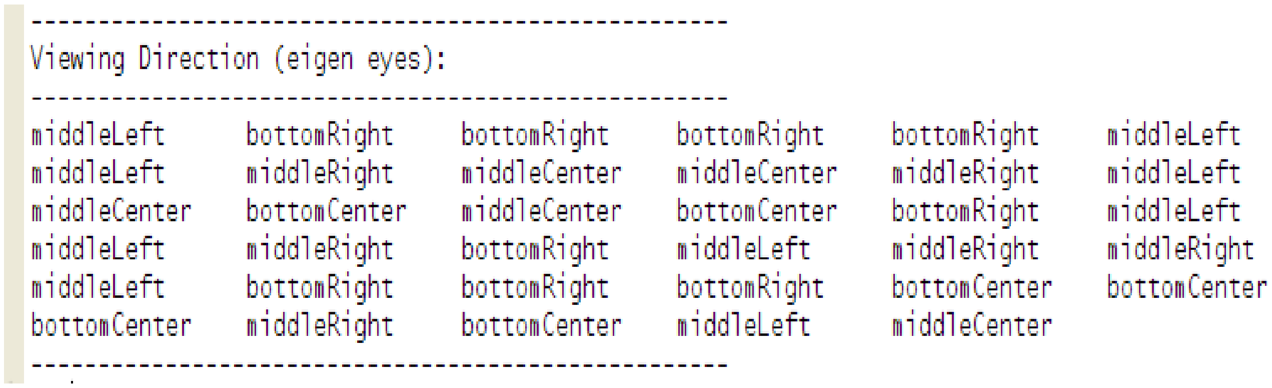


Figure 8: Corresponding best-match training images



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----------------------------------------------------
Viewing Direction (eigen eyes):
----------------------------------------------------
middleLeft      bottomRight     bottomRight     bottomRight     bottomRight     middleLeft
middleLeft      middleRight     middleCenter    middleCenter    middleRight     middleLeft
middleCenter    bottomCenter    middleCenter    bottomCenter    bottomRight     middleLeft
middleLeft      middleRight     bottomRight     middleLeft      middleRight     middleRight
middleLeft      bottomRight     bottomRight     bottomRight     bottomCenter    bottomCenter
bottomCenter    middleRight     bottomCenter    middleLeft      middleCenter
----------------------------------------------------
```

Figure 9: Corresponding best-match gaze direction

This gives 18/35 correct, that is about 51% correct.

Using 5 eigenvalues, we get:

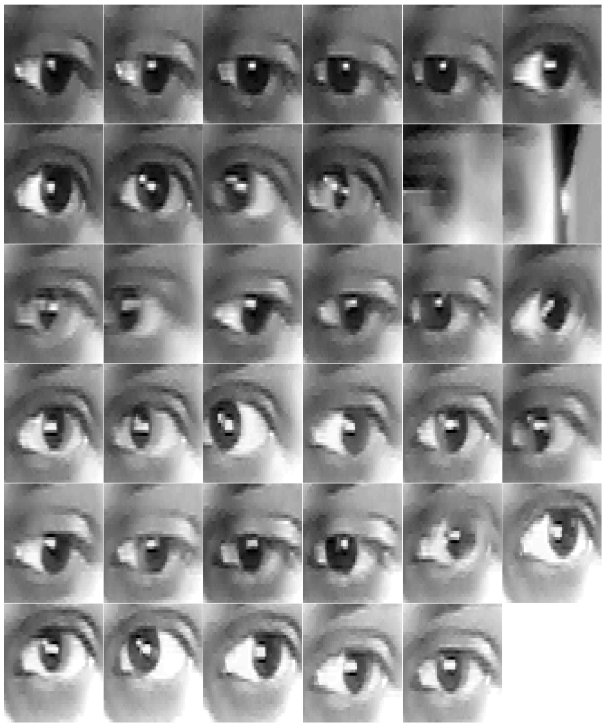


Figure 10: Test images

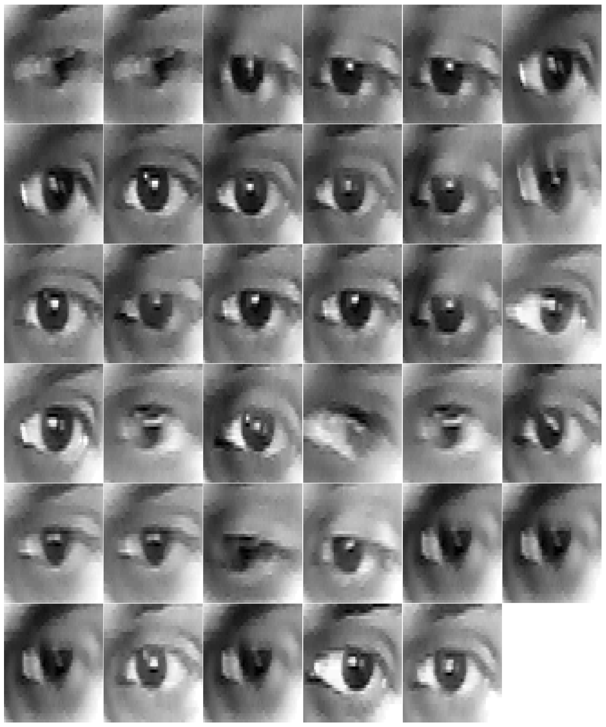
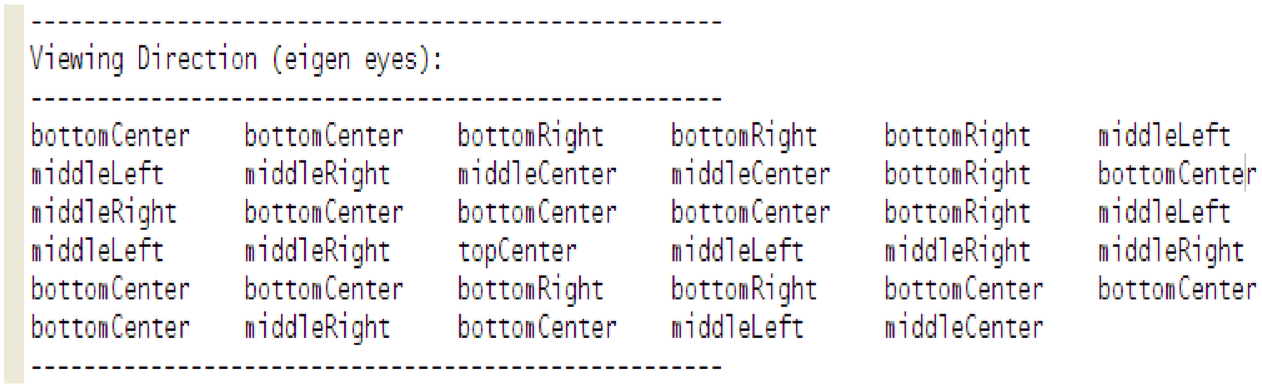


Figure 11: Corresponding best-match training images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Viewing Direction (eigen eyes):
---------------------------------------------------
bottomCenter   bottomCenter   bottomRight    bottomRight    bottomRight    middleLeft
middleLeft     middleRight    middleCenter   middleCenter   bottomRight    bottomCenter
middleRight    bottomCenter   bottomCenter   bottomCenter   bottomRight    middleLeft
middleLeft     middleRight    topCenter      middleLeft     middleRight    middleRight
bottomCenter   bottomCenter   bottomRight    bottomRight    bottomCenter   bottomCenter
bottomCenter   middleRight    bottomCenter   middleLeft     middleCenter
---------------------------------------------------
```
Figure 12: Corresponding best-match gaze direction

This gives 13 out of 35 correct, for a correctness of about 37%.

For the curious, here are the eigen-eyes themselves:

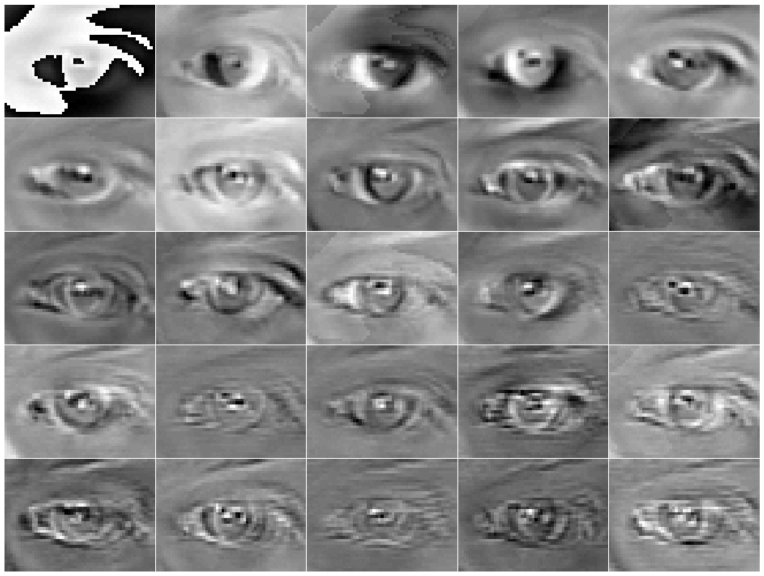


Figure 13: Eigen-eyes

And the following are the reconstructed eyes:

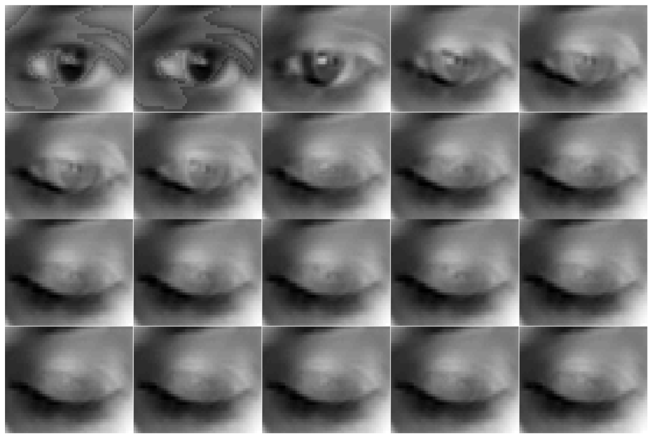


Figure 14: Reconstructed eyes

Hence, our eigen-eyes method works fairly well in tracking the gaze. It is also apparent that the number of principal components is a critical parameter in using this method successfully. The more principal components we can use, the greater the number of choices we have to find matchings from, and hence the better job we can do. At the same time, the effect of increasing the number of principal components plateaus out after about 15-20 principal components, so there is not much reason to optimize after this point.

5.3 SVM

Here are the results of using SVM with the one-versus-one multi-class method and a polynomial kernel function of degree 1:

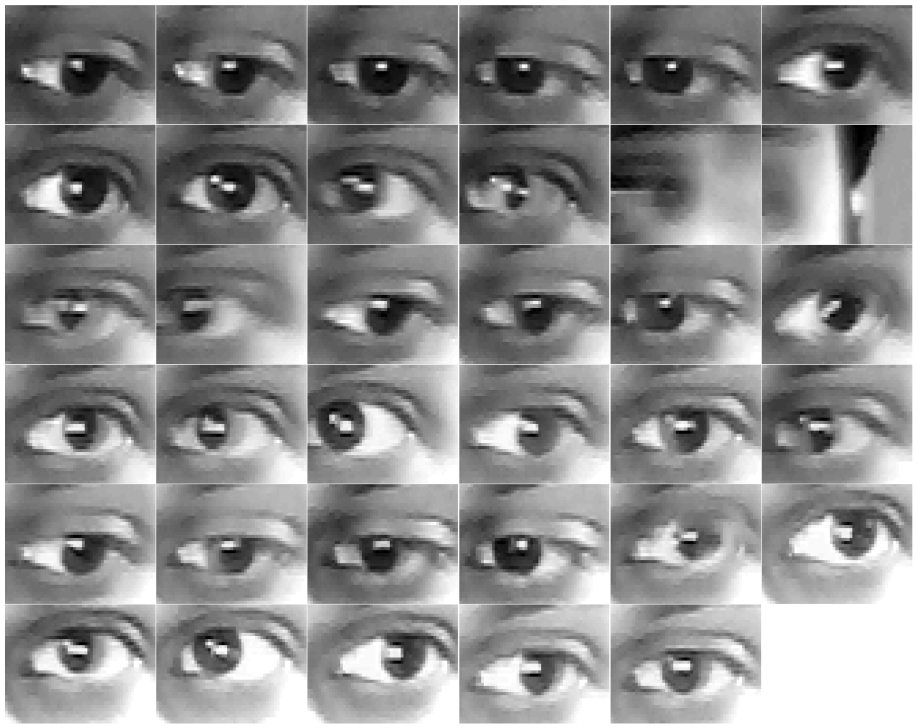
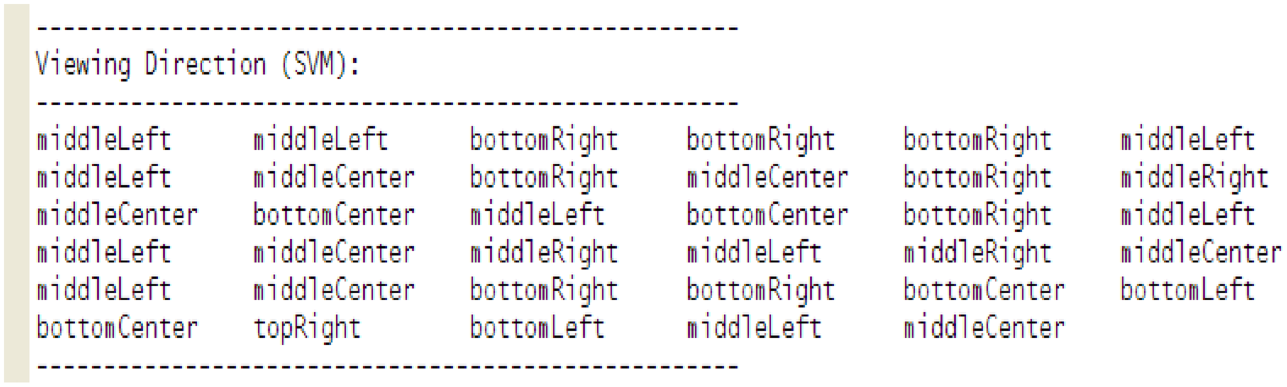


Figure 15: Test images



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----------------------------------------------------
Viewing Direction (SVM):
----------------------------------------------------
middleLeft     middleLeft     bottomRight    bottomRight    bottomRight    middleLeft
middleLeft     middleCenter   bottomRight    middleCenter   bottomRight    middleRight
middleCenter   bottomCenter   middleLeft     bottomCenter   bottomRight    middleLeft
middleLeft     middleCenter   middleRight    middleLeft     middleRight    middleCenter
middleLeft     middleCenter   bottomRight    bottomRight    bottomCenter   bottomLeft
bottomCenter   topRight       bottomLeft     middleLeft     middleCenter
----------------------------------------------------
```

Figure 16: Corresponding best-match gaze direction

This gives 22 correct out of 35, for a correctness of about 62.8%. It is quite interesting to note that this linear polynomial function works quite well, but any polynomial of greater degree fails entirely and just classifies all objects to the same class. This is quite strange behaviour. One could expect a polynomial function of higher degree with a gentle curve (low gradient) could approximate quite well, the job of a linear function. Maybe this arises because of the way the data points are apparently mapped to the higher dimension, causing them to become clumped together.

On using one-versus-all classifier, with the same polynomial kernel, we get:

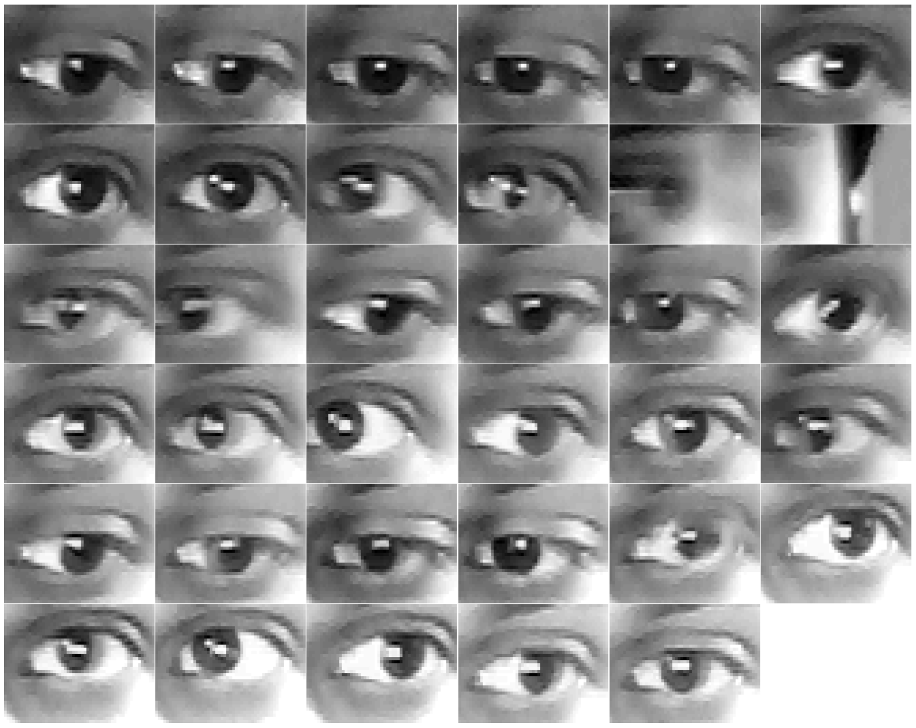
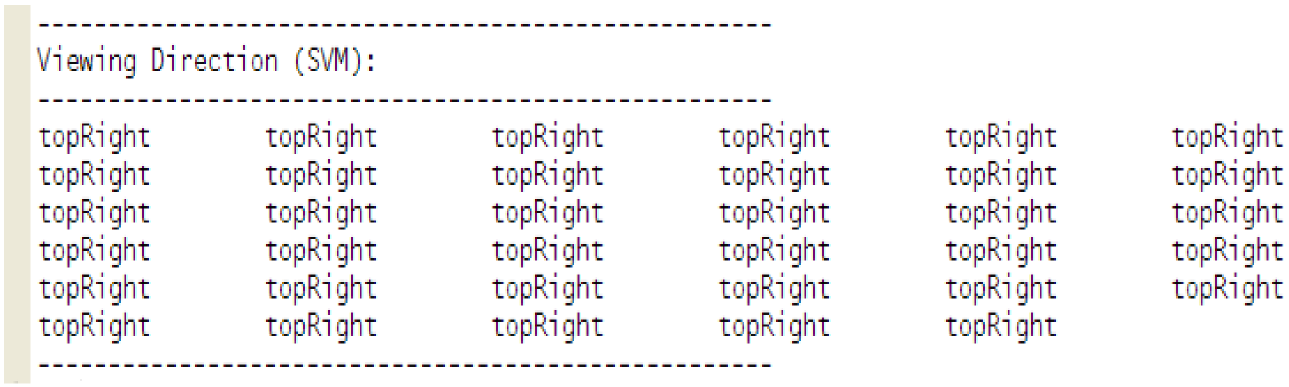


Figure 17: Test images



```
----------------------------------------------------
Viewing Direction (SVM):
----------------------------------------------------
topRight        topRight        topRight        topRight        topRight        topRight
topRight        topRight        topRight        topRight        topRight        topRight
topRight        topRight        topRight        topRight        topRight        topRight
topRight        topRight        topRight        topRight        topRight        topRight
topRight        topRight        topRight        topRight        topRight        topRight
topRight        topRight        topRight        topRight        topRight
----------------------------------------------------
```

Figure 18: Corresponding best-match gaze direction

Here, there is obviously something wrong with the classification process. The SVM classifier has lumped everything together, and simply labelled everything to be the same. The reason behind this could be that the space for training an SVM with all the classes (one-versus-all) may be a lot more complex than one where we are only dealing with two classes (one-versus-one). Hence, the kernel function which emulates the lift to higher dimensionality must be chosen correctly to account for this fact. With the toolbox that we used, none of the given kernel functions actually worked in classifng the data. All of them had similar results to the above. We hope to tackle this befuddling problem in the future.

Here are the results of using SVM with the one-versus-one multi-class method and a homogeneous polynomial kernel function of degree 1:

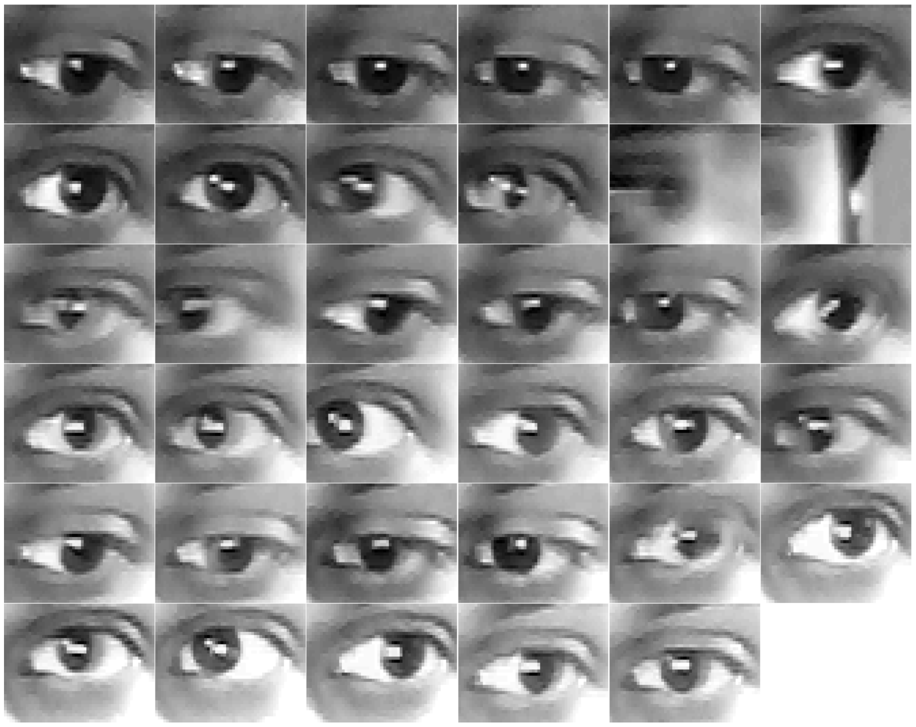
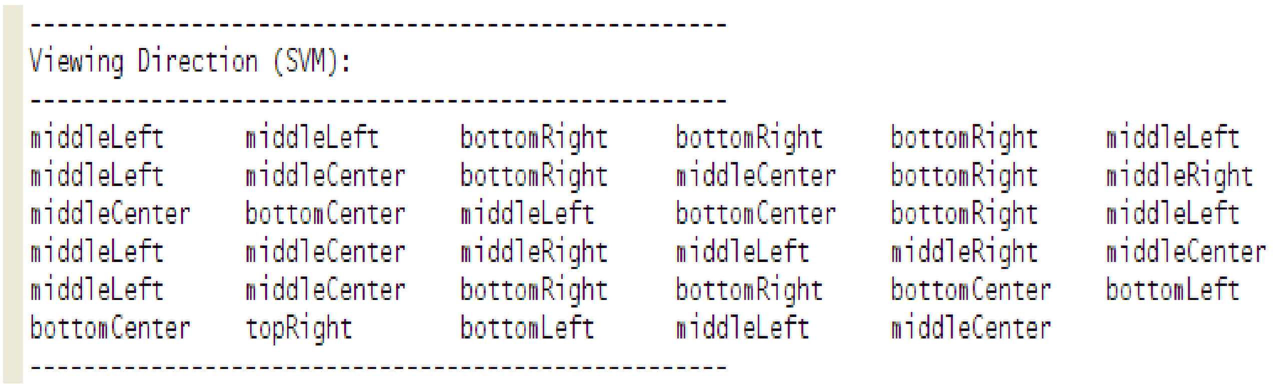


Figure 19: Test images



```
--------------------------------------------------
Viewing Direction (SVM):
--------------------------------------------------
middleLeft     middleLeft     bottomRight    bottomRight    bottomRight    middleLeft
middleLeft     middleCenter   bottomRight    middleCenter   bottomRight    middleRight
middleCenter   bottomCenter   middleLeft     bottomCenter   bottomRight    middleLeft
middleLeft     middleCenter   middleRight    middleLeft     middleRight    middleCenter
middleLeft     middleCenter   bottomRight    bottomRight    bottomCenter   bottomLeft
bottomCenter   topRight       bottomLeft     middleLeft     middleCenter
--------------------------------------------------
```

Figure 20: Corresponding best-match gaze direction

This gives 22 correct out of 35, for a correctness of about 62.8%. This function works quite similar to the related simple polynomial kernel. It also shows similar gibberish results for higher degree functions.

Hence, the SVM classifier does quite well when we appropriately choose the method for doing multi-class classification. Also, the validity of the classification depends on the kernel function we use.

5.4 Summary

We have seen, therefore, that the eye segmentation method works slowly, but does quite a good job of detecting the eye across frames, given a suitable template. On the contrary, the gaze tracking methods work much faster, but aren't nearly as robust. At their most optimized states, they both achieve similar levels of success (around 60% correct classification). Choosing the parameters is important to reach this upper limit; for a lot of choices, the algorithms may just not work at all.

6 Issues and further work

While this gaze tracker is an interesting theoretical project, our motivation was to integrate it without document readers to allow for an auto-scrolling application. As of now, our algorithm is not robust enough to allow for this. We have identified the following issues and potential solutions to them for future work:

1. The gaze tracking algorithm isn't extremely accurate. For a real system, we would need the tracker to work extremely accurately so that the user doesn't have to wait forever for the algorithm to register their cues. We can try to reduce the amount of redundant information the tracker gets, by cropping out all of the eye image except the eye part itself using some variant of circle detector. This will help us get the necessary information - the direction of the eyeball - without other distracting information that may be leading to false positives. We can also look further into other, more robust algorithms like the hybrid PCCR algorithm[8]. This algorithm will further resolve potential issues about invariance to scale and head movement.

2. The eye-segmentation algorithm is relatively slow, since it is correlation based (even though it performs remarkably well). We tried using alternative approaches such as Hough transforms, but those were slow as well. We will have to research further and look for faster and equally robust methods, possibly using a variety of less complex algorithms, like edge detectors.

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