Discrete Gaze-Estimation using Machine Learning

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Abstract. Abstract goes here

Keywords: Batman

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1 Introduction

We will perform an experiment where a subject is looking at a finite amount of points under different conditions. These conditions are combinations of moving the head or keeping it still and an infrared light being on or off. The images will then be processed to identify the edges of the eye and the center of the pupil. We can then extract eye images using the feature data. We can then run machine learning algorithms on the data and analyze the results to determine if we are able to perform gaze estimation.

This report will explain concepts of machine learning utilized in this project, the experiment in more detail, how the results can be evaluated, possible threats to validity and the final results.

2 Problem Description

In this project we will determine under what conditions it is possible to perform gaze estimation using machine learning.

Gaze estimation is the process of identifying where an eye is looking. It has a lot of applications, for example in giving disabled people the ability to type with, and control devices using, their eyes. Especially people with Amyotrophic Lateral Sclerosis (ALS) can make use of this technology. It is also closely related to eye tracking where image analysis is used to identify eyes and eye features such as eye corners, center of the iris, glints in the eye and so on. We will not be using eye tracking as it is outside the scope of this project.

Using machine learning for gaze estimation can be problematic, as images of faces (or eyes) are high-dimensional data, making learning complex and expensive. There are a few approaches to reducing the complexity. One could reduce the input space by converting the image to grayscale, isolating the eye-pixels from the rest of the image, and scaling the resulting image. One could also reduce the input space by extracting features of the eye such as the positions of the corners of the eye and the center of the pupil. In this project we attempt both approaches.

When gathering test data there are also many factors to consider. Test subjects should be placed similarly in such a way that their eyes are clearly visible to the camera and at a distance where the reflection from the infrared lights can be seen. The angle of the head and eyes also impacts the resulting images. Lighting is also very important and should be consistent during testing.

When processing the initial test data, it can be beneficial to histogram equalize the images to increase the contrast.

3 Theory

Theory goes here.

4 Technical Solution

Technical solution goes here.

5 Evaluation

Evaluation goes here.

6 Discussion

6.1 Internal

Learning only tested on eyes from 2 people. Eye corners and pupil center was manually marked, not all marked 100% accurately. Webcam images were not of very high quality. This makes the potential usability cheaper which is a plus, but some detail may be lost. Our test setup required the test-subjects to sit a certain distance from the camera for the infrared lights to be visible. This had the effect that the eye were a smaller part of the input images than they could have been. To simplify learning, images were scaled down to 20x20 pixels. Information lost that could potentially have an impact on learning. Trade-off. Noise due to loose experiment setup. Even during head-still images the heads moved slightly etc.

6.2 External

Other ethnicities (in particular asians?) could potentially give different results. Given proper test-setup, it is unlikely to have any significant effect. "individuality of the eyes, variability in shape, scale, location, and lighting conditions"

7 Related Work

Related work goes here.

8 Conclusion

No lights head move - Not separable No lights head still - Left/right separable, PCA 1-2, 2-3, 2-4, 2-5 With lights head move - Not separable With lights head still - Separable, PCA 1-2, 2-3, (2-4), ((2-5))