Eye detection in complex environments using Gabor filters

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Abstract—Eye detection has many applications in computer vision systems. In this article, we propose an eye detection algorithm that trains Gabor filters to describe eye features and later detect eyes in unconstrained environments. Skin color information detects image regions that have higher probabilities of containing eyes. The Chromatic colour space will be used to train the system to model skin colour. Separable Gabor filters are used to decrease computation time. Graphics processing hardware (GPU) is used to accelerate the algorithm to create an interactive experience.

Index Terms—Eye detection, Gabor filters, Chromatic colour space

I. INTRODUCTION

Eye detection has applications in facial recognition, security authorisation systems, human robot interaction, head pose estimation, driver drowsiness or sleep detection and many more. Eye detection used in controller-less computer game interaction is revolutionizing the computer gaming industry.

In recent years, there have been various methods proposed to detect eyes in images. These methods can be broadly classified into the following four categories: Template matching methods[1], Infrared illumination methods[2], Feature based methods and Statistical methods. Some examples of statistical methods are Support Vector Machine (SVM)[3], Principal Component Analysis (PCA)[4], Eigenfaces[5] and Gabor filters[6]. In this paper a new method for eye detection in complex environments is proposed. An input image is transformed into an appropriate color space and compared to a skin color trained database. Skin color information in the input image is used to localize facial candidates, these candidate areas will then be convolved with Gabor filters to localize the potential eye regions.

II. SKIN COLOUR MODELING

In order to segment possible facial candidate regions in images, a skin colour model must be developed that can classify skin regions from non-skin regions in images. It is important that the skin color model is compensating to different ethnic groups and is invariant to lighting conditions. In most cases images that contain skin have small variances in colour on the skin regions but can have larger variances in luminance caused from lighting conditions. Therefore a colour space that is luminance invariant is ideal. The Chromatic color space is a two dimensional colour space that normalizes colours to make it robust against change in luminance[7].

1) Chromatic colour space: Luminance is avoided by using the chromatic colour space. Chromatic colours, also known as "pure" colours, are defined in the following way:

\[
Cr = \frac{R}{R + G + B}
\]

\[
Cb = \frac{B}{R + G + B}
\]

Now that a suitable colour space has been chosen it must be trained to model skin colour. Skin colours from multiple ethnic groups must be included in training for more robust results. Care must be taken when choosing which skin colours to include in training so that the very dark and very light colours are excluded, these colours can lead to detection of false positives.

![Fig. 1. (a) Input Image (b) Skin results (c) Closing noise reduction on (b)](image)

From Fig.1 you can see the results of the chromatic colour skin model. Noise reduction and closing operations are performed on Fig.1 (b) which produce a more accurate result which can be seen in Fig.1 (c).

III. GABOR FILTERS

A. Gabor Filters

Gabor filters have traditionally been used for texture segmentation and classification[8], fingerprint recognition[9] and face recognition. There are other variations of Gabor filters for eye recognition called Ring Gabor Filters (RGF) and Circular Gabor Filters (CGF)[10]. Gabor filters are
defined to have both frequency selective and orientation selective properties. Gabor filters are composed of a Low pass filter and a band pass filter which are defined as follows:

Real part

\[
G(x, y, \theta, f_0) = \exp \left[ -\frac{1}{2} \left( \frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2} \right) \right] \cos(2\pi f_0 x') \tag{3}
\]

Imaginary part

\[
G(x, y, \theta, f_0) = \exp \left[ -\frac{1}{2} \left( \frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2} \right) \right] \sin(2\pi f_0 x') \tag{4}
\]

where

\[
x' = x \cos \theta + y \sin \theta \tag{5}
\]

and

\[
y' = -x \sin \theta + y \cos \theta \tag{6}
\]

The \( \theta \) is the selective orientation of the Gabor filter respective to the vertical axis. \( f_0 \) is the selective frequency of the Gabor filter along the \( x' \) axis. The \( \sigma_x \) and \( \sigma_y \) are the standard deviations of the Gaussian function along the \( x' \) and \( y' \) axis respectively. \((x,y)\) is the center of the respective field in the spacial domain.

Fig. 2. A visual representations of Gabor filters in eight orientations between 0 and \( \pi \) radians

IV. PRELIMINARY RESULTS

As seen in Fig.3 an example of the preliminary result for eye detection is provided. Detection of potential eye region were achieved with a limited training using Gabor filter responses

V. FUTURE WORK

Training the Gabor filters with larger data sets will yield a better eye descriptor which should reduce false positive detection. The results for skin detection and Gabor filters are separate, we are busy combining these results which will yield more accurate results. A GPU implementation of separable Gabor filters is being developed which will decrease computation time.

Fig. 3. Detection of potential eye regions

REFERENCES


Jacques de Villiers is currently finishing the final year of his undergraduate, he is studying towards a BSc Information Technology at the University of Johannesburg (UJ). After competing in the Image Processing Challenge at UJ in 2010 he was invited to become a junior researcher at the HyperVision Research Lab. His current research includes GPGPU programming, eye detection, face detection and virtual windowing.