Lecture given by Prasad due to NSF panel travel.

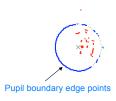
The general thrust is relevant for the exam.

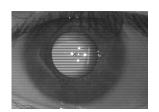
### Computer vision based eyegaze tracking

Prasad Gabbur

#### Pupil (ellipse) tracking

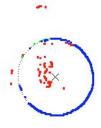
- Pupil center is a feature for eye-gaze estimation
- Track pupil boundary ellipse

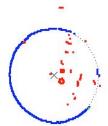




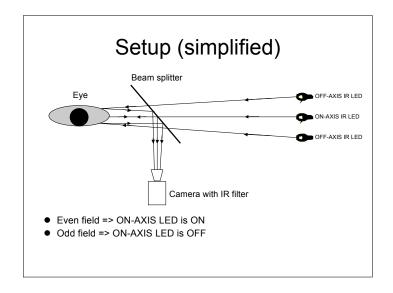
Ellipse overlaid on the eye image

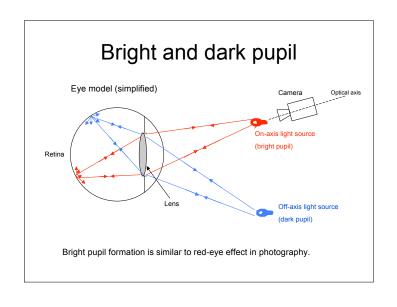
# Ellipse fitting and tracking in the presence of outliers

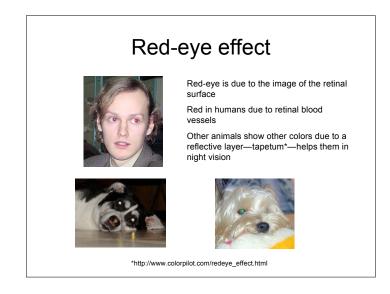


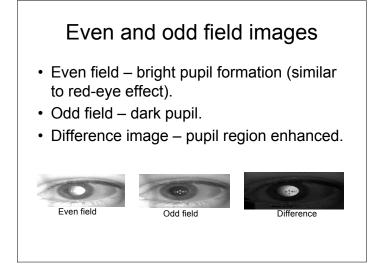


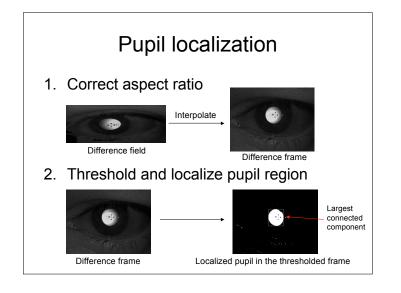
- · Seems easy?
- · Hard problem!
  - Presence of noisy data and outliers





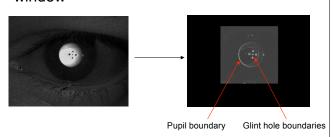






#### Pupil edge detection

Gradient magnitude within the processing window



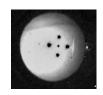
• Large gradient magnitude => potential edge

## Ellipse fitting

- · Bunch of points
  - How to fit an ellipse?
  - Noise in localization
  - Outliers
- Hough transform
  - Time intensive!
- Least squares
  - Minimize sum squared of some distance measure (?)

#### Pupil edge detection

- Radial edge detection with hysteresis
  - 180-200 edge points
  - spurious edge pixels (e.g., glint hole boundary)



Radial edge detection with hysteresis



#### Algebraic Distance (AD)

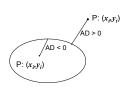
Equation of ellipse

$$F(x,y) = ax^{2} + bxy + cy^{2} + dx + ey + f = 0$$
 (Conic)  

$$4ac - b^{2} > 0$$
 (Constraint for ellipse)

Algebraic distance

$$AD(x_i, y_i) = F(x_i, y_i) = ax_i^2 + bx_iy_i + cy_i^2 + dx_i + ey_i + f$$



To avoid sign of AD, use squared AD:  $AD^2(x_i, y_i) = F^2(x_i, y_i)$ 

#### Least squares ellipse fitting

· Edge points:  $(x_i, y_i), i = 1...N$ 

· Minimize sum of square of ADs:

$$E = \sum_{i=1}^{N} F^2(x_i, y_i)$$

- Possible to convert to linear least squares (?)
  - Non-homogeneous
  - Homogeneous

#### Least squares ellipse fitting

$$AD(x_i, y_i) = F(x_i, y_i) = ax_i^2 + bx_iy_i + cy_i^2 + dx_i + ey_i + f$$

$$AD(x_i, y_i) = \begin{bmatrix} x_i^2 & x_i y_i & x_i^2 & x_i & y_i & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} = u_i^T p$$

Possible to convert to linear least squares (Homogeneous)

#### Least squares ellipse fitting

$$U = \begin{bmatrix} u_1^T \\ u_2^T \\ \vdots \\ u_N^T \end{bmatrix} \qquad p = \begin{bmatrix} a \\ b \\ c \\ d \\ e \end{bmatrix}$$

• Minimize  $E = \sum_{i=1}^{N} F^{2}(x_{i}, y_{i}) = (Up)^{T} Up = p^{T} U^{T} Up$ 

• Inequality constraint  $4ac-b^2 > 0$ 

$$4ac - b^2 > 0$$

Equality constraint

$$4ac - b^2 = 1$$

- Avoid trivial solution p = 0

- Force a scale on p because if p is a solution, then any scalar multiple of  $\hat{p}$  is also a solution

#### Least squares ellipse fitting

• Quadratic constraint  $4ac-b^2=1$ 

is equivalent to\*

$$p^T C p = 1$$

\* Fitzgibbon et al, "Direct least squares fitting of ellipse", PAMI 1999.

#### Least squares ellipse fitting

Solution is the positive generalized eigenvector of

$$U^T Up = \lambda Cp$$

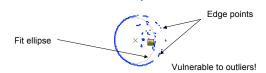
- Least squares
  - Is it a perfect (flawless) solution?
  - Problems?

#### **RANSAC**

- Robust statistical model selection technique in the presence of outliers
- Idea
  - Fit model using minimum # training points chosen at random
  - Evaluate the model against the remaining points according to an error threshold
  - Points agree (consensus) or disagree (outlier)
  - Compute % of consensus points
  - Repeat the above for certain #iterations
  - Keep the model with the highest % consensus
  - Refit using consensus + training

#### Least squares ellipse fitting

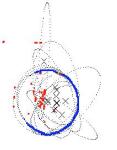
• Direct least squares ellipse fitting\*



- Use RANSAC (robust to outliers)
  - Random (RAN) Sample (SA) Consensus (C)
  - \* Fitzgibbon et al, "Direct least squares fitting of ellipse", PAMI 1999.

#### RANSAC for ellipse fitting

- Min # of training points: 6
- Randomly sample
- Fit using least squares
- Evaluate
- · Choose the best

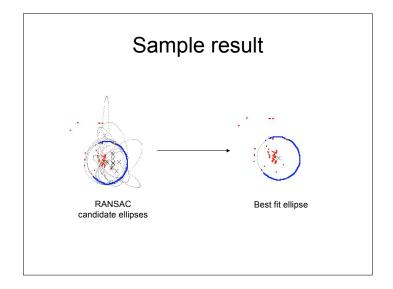


#### **RANSAC**

· Number of iterations

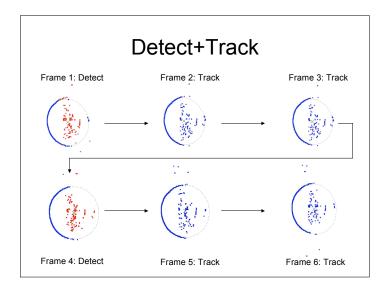
$$n = \frac{\log(1-\varepsilon)}{\log(1-\alpha^k)}$$

- *n* Number of iterations
- $\varepsilon$  Probability of finding at least one outlier free sample
- $\alpha$  Probability of inliers in your data
- k Number of training points sampled every iteration



### Tracking

- Brute force: Detect ellipse every video frame
  - RANSAC: Computationally intensive
- Better: Detect + Track
  - Ellipse usually does not change too much between adjacent frames
- Principle
  - Detect ellipse in a frame
  - Predict ellipse in next frame
  - Refine prediction using data available from next frame
  - If track lost, re-detect and continue



# Tracking example

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