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Eyelids and eyelash detection based on clusterization of vector of local features

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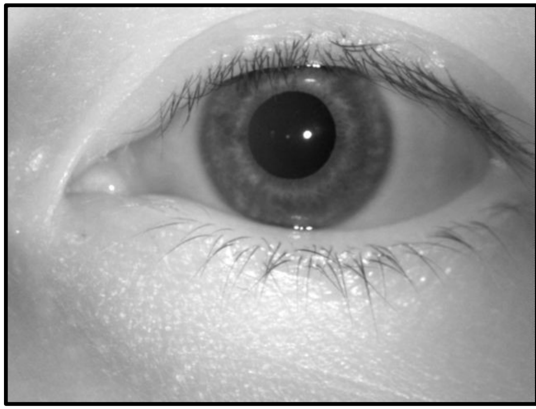
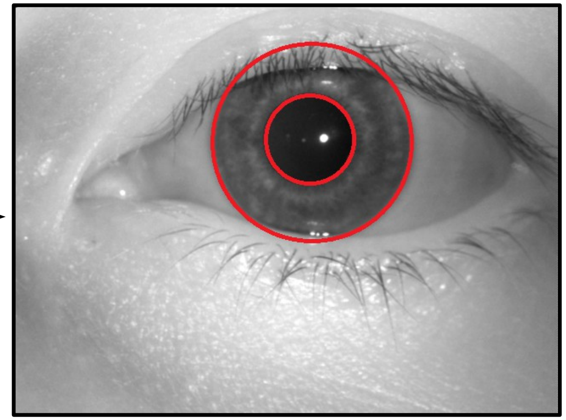
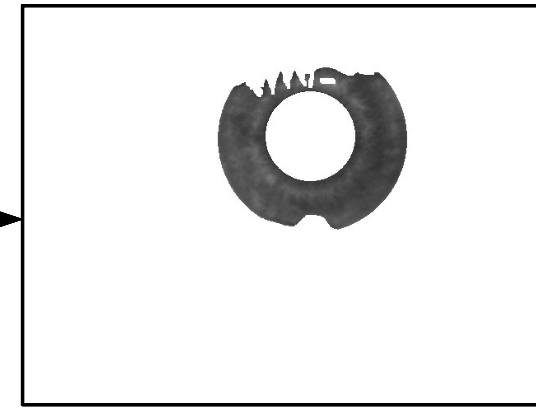
The role of occlusion detection



Source image



Borders



Occlusion mask

Lower precision of recognition due to irrelevant data

Higher precision of recognition

Related work

Min T.-H., Park R.-H. Comparison of eyelid and eyelash detection algorithms for performance improvement of iris recognition // Pattern Recognition Letters. 2009. V.30. N.12. P.1138–1143.

Detection of occlusion as:

- Straight line segment of the iris circle
- Parabolic (or other parametric curve) segment
- Adaptive curve (active contour) segment
- Area of pixels i.e. occlusion mask

Detection of occlusion by:

- Brightness projection
- Gradient map inside iris
- Gradient direction at the iris border
- Matching images in sequence
- Local texture features

Our approach

Area of pixels , local features

Unsupervised learning scheme → Clusterization

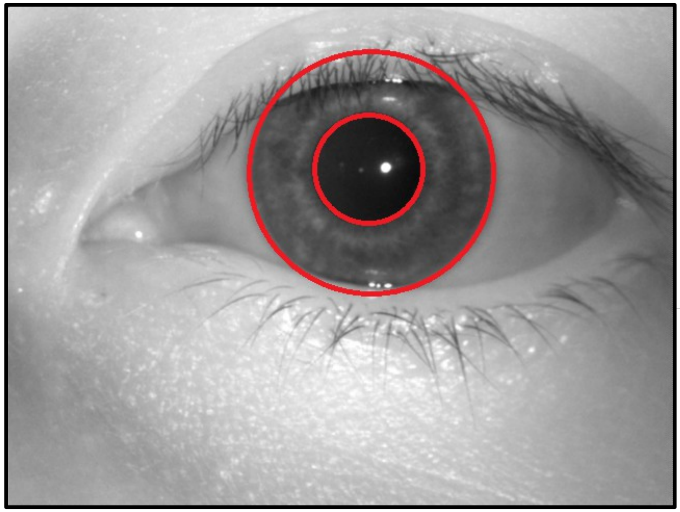
Proposition 1: Iris texture is similar across whole open area

Proposition 2: Occluded areas may have various textures

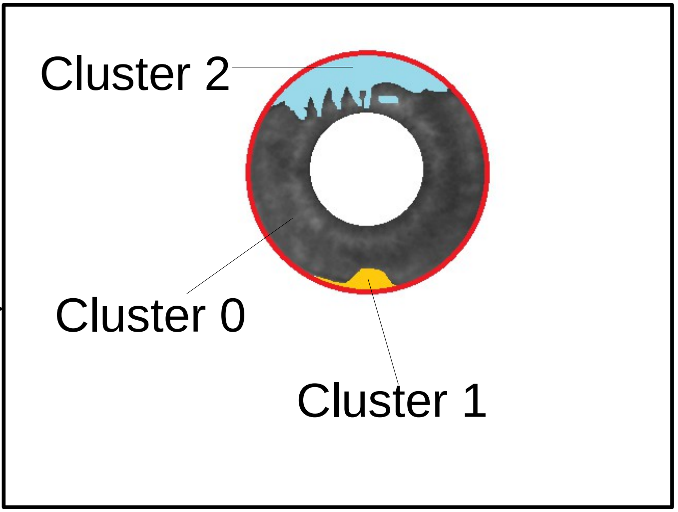
Proposition 3: Iris texture in open area differs from those in occluded areas

Proposition 4: Iris open area is a simply connected (single-piece) set of pixels

Problem statement



Clusterization by local texture features



Grayscale image $I(x, y)$

Iris inner border $(x, y, r)_P$

Iris outer border $(x, y, r)_I$

List of pixels belonging to cluster 0

or

Indicator function:

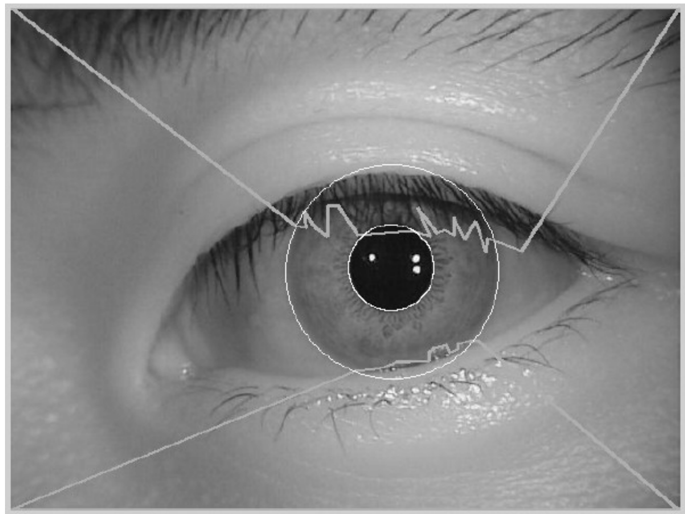
$$C(x, y) = \begin{cases} 1, & (x, y) \in C_0 \\ 0, & otherwise \end{cases}$$

Parameters of the approach:

- Local texture features
- Clusterization method
- Number of clusters
- Distance metric for clusterization

Quality criteria

Expert marking



Occlusion is marked as a poly-line.
One can create a «ground thuth» indicator:

$$\hat{C}(x,y)=\begin{cases}1, & (x,y)\in\hat{C}_0\\ 0, & otherwise\end{cases}$$

Relative error of the first kind: share of points in the open area, which are erroneously classified as occlusion

$$E_1=\frac{\{|(x,y):C(x,y)=0,\hat{C}(x,y)=1|\}}{\{|(x,y):\hat{C}(x,y)=1|\}}$$

Relative error of the second kind: share of points in the occluded area, which are erroneously classified as opened

$$E_2=\frac{\{|(x,y):C(x,y)=1,\hat{C}(x,y)=0|\}}{\{|(x,y):\hat{C}(x,y)=0|\}}$$

$$E_1+E_2\rightarrow min$$

$$Q=\sum_{i=1}^{N}1-E_1(I_i)+E_2(I_i)\rightarrow max$$

Local texture features

Average brightness in local neighborhood

Mean square deviation in local neighborhood

Variance (max-min) in local neighborhood

Components of Markov transition matrix in binarized local nbhood

Normalized distance to pupil center

Principal components of local texture

Clusterization methods

k-means

k-medoids

Hierarchical

Distance metrics

Euclidian

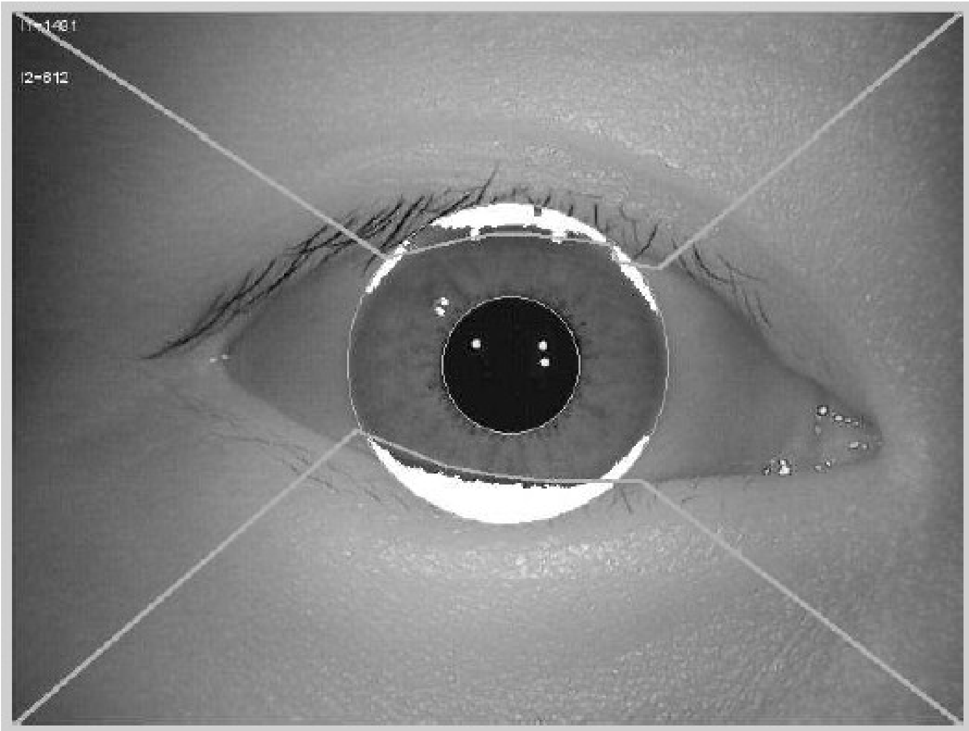
Chebyshev

City-block

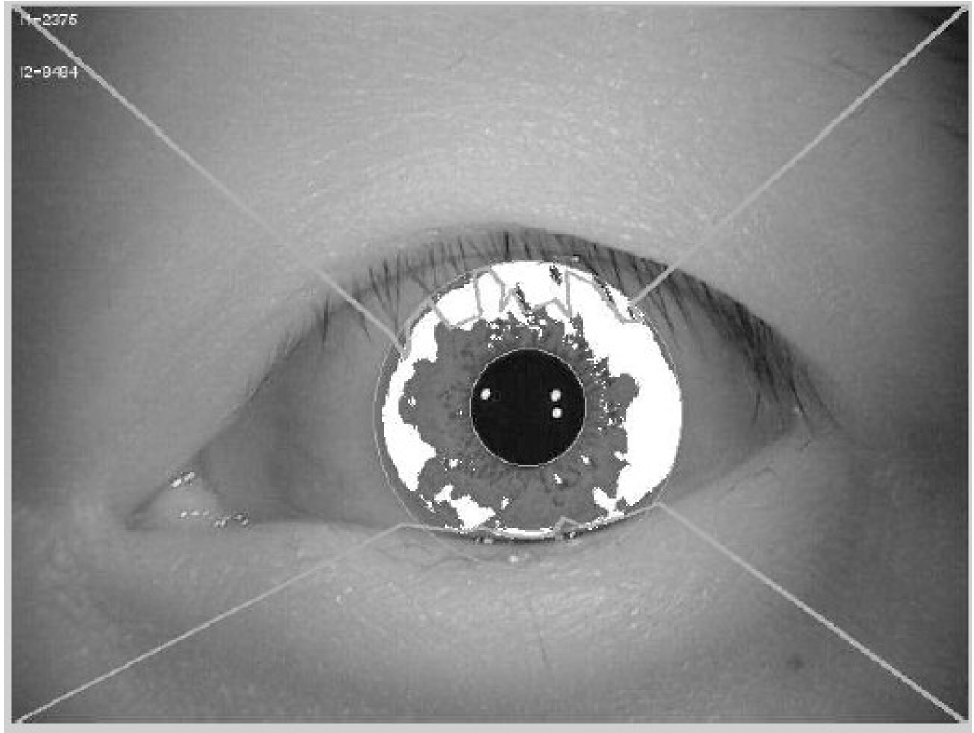
Mahalonobis

Cosine

Sample results



Good



Poor

Result statistics

Method	Distance	$Q \pm \Delta Q$
k-means	Euclidian	0,707 ± 0,006
	City block	0,683 ± 0,008
	Cosine	0,718 ± 0,008
	Correlation	0,718 ± 0,008
k-medoids	Normalized Euclidian	0,721 ± 0,008
	Euclidian	0,703 ± 0,006
	City block	0,684 ± 0,008
	Minkovsky	0,680 ± 0,008
	Chebyshev	0,685 ± 0,008
	Mahalonobis	0,652 ± 0,011
	Cosine	0,719 ± 0,009
	Correlation	0,718 ± 0,009

K=2

Method	Distance	$Q \pm \Delta Q$
k-means	Euclidian	0,784 ± 0,003
	City block	0,785 ± 0,004
	Cosine	0,764 ± 0,007
	Correlation	0,760 ± 0,007
k-medoids	Normalized Euclidian	0,804 ± 0,005
	Euclidian	0,779 ± 0,004
	City block	0,787 ± 0,004
	Minkovsky	0,782 ± 0,004
	Chebyshev	0,779 ± 0,004
	Mahalonobis	0,775 ± 0,006
	Cosine	0,762 ± 0,007
	Correlation	0,755 ± 0,008

K=3

Result statistics

Method	Distance	$Q \pm \Delta Q$
Hierarch.	Normalized Euclidian	0,704 ± 0,035
	Euclidian	0,696 ± 0,067
	city block	0,671 ± 0,084
	Minkovsky	0,665 ± 0,055
	Chebyshev	0,675 ± 0,047
	Mahalonobis	0,649 ± 0,061
	Cosine	0,662 ± 0,072
	Correlation	0,655 ± 0,077

K=2

Method	Distance	$Q \pm \Delta Q$
Hierarch.	Normalized Euclidian	0,721 ± 0,035
	Euclidian	0,716 ± 0,053
	city block	0,691 ± 0,078
	Minkovsky	0,675 ± 0,049
	Chebyshev	0,681 ± 0,052
	Mahalonobis	0,658 ± 0,058
	Cosine	0,672 ± 0,070
	Correlation	0,662 ± 0,073

K=3

BEST

Method	Distance	$Q \pm \Delta Q$
k-means	City block	0,785 ± 0,004
k-medoids	Normalized Euclidian	0,804 ± 0,005
Hierarchical	Normalized Euclidian	0,721 ± 0,035

More things to do

- More local texture features (probably selected by convolutional neural nets

- Better parameter optimization (genetic algorithms?)

- Testing by «tagret quality» i.e. by using the obtained masks in template creation&matching process and looking at resulting EER