Improved Iris Segmentation based on Local Texture Statistics.

(Invited Paper)

Vishnu Naresh Boddeti
Electrical and Computer Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Email: naresh@cmu.edu

B.V.K. Vijaya Kumar
Electrical and Computer Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Email: kumar@ece.cmu.edu

Krishnan Ramkumar
Mathworks Inc
Natick, MA 01760-2098
Email: krishnan.ramkumar@mathworks.com

***Abstract*—High performance human identification using iris biometrics requires the development of automated algorithms for robust segmentation of the iris region given an ocular image. Many studies have shown that iris segmentation is one of the most crucial element of iris recognition systems. While many iris segmentation techniques have been proposed, most of these methods try to leverage gradient information in the ocular images to segment the iris, rendering them unsuitable for scenarios with very poor quality images. In this paper, we present an iris segmentation algorithm, which unlike the traditional edge-based approaches, is based on the local statistics of the texture region in the iris and as such is more suited for segmenting poor quality iris images. Our segmentation algorithm builds upon and adapts the seminal work on Active Contours without Edges [6] for iris segmentation. We demonstrate the performance of our algorithm on the ICE [2] and FOCS [1] databases.**

I. Introduction

Iris recognition has proven to be a very reliable cue for person identification due to its unique and intricate texture pattern. The main components of an iris recognition system are iris segmentation, iris feature encoding and feature matching. The performance of the system as whole has been found [4] to be heavily influenced by our ability to segment and extract the iris region from the eye. Many iris segmentation algorithms have been proposed to segment iris regions from good quality iris images, often with impressive segmentation performance. However as iris recognition systems look to be used under more challenging scenarios, such as image acquisition under visible illumination or long range iris recognition scenarios, iris segmentation has proven to be the primary bottleneck in achieving acceptable iris recognition performance.

There exists a vast body of work on iris segmentation. Initial work on iris segmentation models in the literature assumed that the pupil, iris and eyelid boundaries are circular or elliptical in shape, thereby focusing on determining model parameters that best fit these hypotheses. Techniques like the integro-differential operators (a variation of Hough transforms) and its derivatives [7] worked well under ideal image acquisition conditions where there is a significant contrast between the pupil and the sclera regions. Soon models algorithms fitting more general active contour models have been proposed[3], [8], [11]. Taking a different direction, in [10] takes a classification approach to iris segmentation for iris images captured in the visible spectrum.

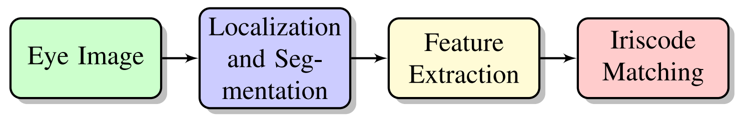

Fig. 1. Iris Recognition Pipeline:

The active contour based methods yield state-of-the-art performance for iris segmentation and have been shown to work extremely well under reasonable image acquisition conditions due to their ability to assume any shape and segment multiple objects simultaneously. The effectiveness of these approaches depends greatly on exploiting the gradient information between the pupil and iris regions as well as the iris and sclera regions which depends on the presence of high contrast between the respective regions. However under challenging imaging conditions like low light, moving subjects etc, which are common in long range image acquisition scenarios the edge information in these images is degraded to the point of there not being a discernible edge, which makes iris segmentation a very challenging task and rendering the previously proposed active contour based iris segmentation algorithms ineffective. In this paper we address this problem by proposing an active contour method for iris region which does not depend on sparse gradient information but instead depends on the texture statistics within the region.

The remainder of the paper is organized as follows. In Section II we describe the iris recognition process briefly and in Section III we describe our proposed iris segmentation algorithm. Experimental results demonstrating the effectiveness of our approach are detailed in Section IV and we finally conclude in Section V.

II. Iris Recognition

An iris recognition system comprises of the following subtasks, iris segmentation, feature encoding and feature matching as shown in Fig. 1. Iris segmentation being the first step in the pipeline, is also the most important component of the whole system. Iris segmentation involves detecting and isolating the

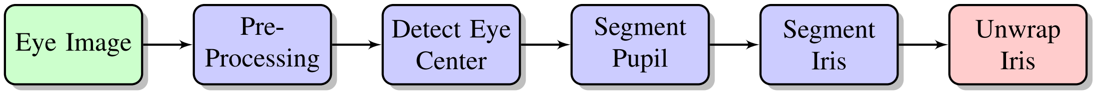

Fig. 2. Iris Segmentation Pipeline of the Proposed Approach

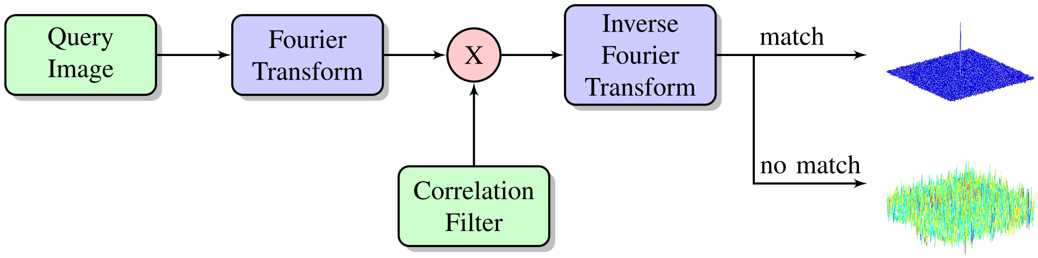

Fig. 3. Correlation filter design principal.

iris structure from an image of the eye, which in turn involves detecting the inner and outer boundaries of the iris. The extracted iris is feature coded by applying (convolution) a set of carefully chosen parametrized complex Gabor filters and phase quantizing the resulting response to result in a binary code.

$$g(\rho, \phi) = \exp\left[-\frac{1}{2}\left(\frac{\rho^2}{\sigma_\rho^2} + \frac{\phi^2}{\sigma_\phi^2}\right) - j\rho(\omega \sin\theta) - j\phi(\omega\cos\theta)\right]$$

where (ρ, ϕ) denotes the polar domain where the filter is applied to the iris pattern. Here θ denotes the wavelet orientation, σ_ρ and σ_ϕ denote the wavelet widths in radial and angular directions, respectively and ω denotes the modulation frequency of the wavelet. Now, given two feature encoded iris templates (binary codes) I_1 and I_2 and bit masks M_1 and M_2 (denoting bits to be ignored), the match score between them is computed via the Normalized Hamming Distance,

$$HD = \frac{\|I_1 \oplus I_2 \cap M_1 \cap M_2\|}{\|M_1 \cap M_2\|} \quad (1)$$

where $\oplus$ denotes an XOR operation and $\|\ \|$ denotes the weight (i.e.,the number of nonzero elements) of the binary code.

III. Proposed Approach

The performance of iris recognition systems is greatly dependent on the ability to isolate the iris from the other parts of the eye such as eyelids and eyelashes, since errors in segmentation may result in inferior recognition performance due to inaccurate encoding of the textural content of the iris. As mentioned previously, commonly used iris segmentation techniques [8] use some variant of edge detection methods which fail to perform well under challenging imaging conditions.

To alleviate this problem, we propose a region-based active contour segmentation based on the seminal work of Chan and Vese [6] and some recently proposed improvements [12] to it. The proposed technique segments the image based on the distribution of pixel intensities or features extracted from the eye image from a region both inside and outside the contour rather than looking for sharp edges, making it more robust to blurring and illumination variations than an edge-based active contour. Our iris segmentation pipeline shown in Fig.2 involves an image pre-processing step, followed by eye center detection which feeds into the pupil segmentation module whose result finally feeds into the iris segmentation module.

A. *Pre-Processing*

Illumination variation poses significant challenges to reliably segment the outer and inner boundaries of the iris, for example when the image contrast is very low, which is especially so under challenging imaging conditions. To increase the contrast between the different regions of the ocular image, we first perform simple illumination normalization which helps make intensity variation across different images more uniform, thereby improving the stability of our segmentation algorithm.

B. *Eye Center Detection*

The proposed active contour based iris segmentation algorithm needs a contour initialization within the pupil of the eye. For this purpose we use a correlation filter based eye center detector for this purpose. A correlation filter (CF) is a spatial-frequency array (equivalently, a template in the image domain) that is specifically designed from a set of training patterns that are representative of a particular class. These filters are designed to ideally produce outputs with sharp peaks at the eye center and zeros everywhere else in the correlation plane (See Fig.3 for an illustration). More details about the explicit filter design can be found in [5]. The correlation filter for the eye center detector was trained on 1,000 images, in which the eye centers were manually labeled. The correlation filter approach resulted in a success rate of over 95% when applied on the full FOCS dataset. Fig. 4 shows a typical image after eye center detection, where the eye center is shown with a small green dot and Fig. 5 show some of the rare cases where the eye center was not accurately determined. We must note that the accuracy of our iris segmentation method is crucially dependent on the correctness of eye center detection, therefore having a very robust eye center detector is important.

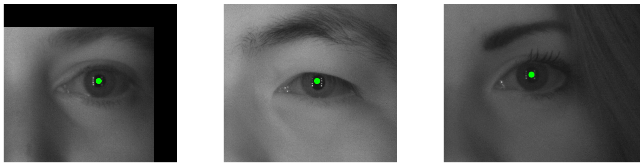

Fig. 4. Eye Detection Results: Successful Cases

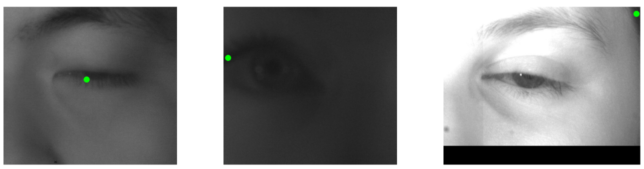

Fig. 5. Eye Detection Results: Failed Cases

C. Active Contours Without Edges

The basic idea of active contour models relies on detecting salient objects by evolving a curve or a surface subject to image based constraints. Let $\Omega \in \mathbb{R}^d$ be the image domain and $I : \Omega \to \mathbf{R}$ be a given image function. In [9], Mumford and Shah proposed an energy functional to be minimized by a suitable contour C in Ω for image segmentation.

$$E(I, C, \Omega) = \int_{\Omega} |I - I_0|^2 dx + \lambda \Gamma(C) \tag{2}$$

where $\Gamma(C)$ is a regularization function for the contour C and λ is a non-negative constant weight. Minimizing the above energy function E results in an optimal contour that segments the image into a piecewise smooth image I that approximates the original image I_0. In [6] Chan and Vese proposed an active contour model for segmenting images containing objects that have poor boundaries by proposing to minimize the following piecewise constant approximation to the Mumford and Shah energy function,

$$\begin{aligned} E(I, C, \mu, \bar{\mu}, \lambda_1, \lambda_2) &= \int_{\Omega_{out}} |I - \bar{\mu}|^2 dx \\ &+ \lambda_1 \int_{\Omega_{in}} |I - \mu|^2 dx + \lambda_2 \Gamma(C) \end{aligned} \tag{3}$$

where Ω_{in} and Ω_{out} represents the region inside and outside the contour C and μ and $\bar{\mu}$ are two scalar constants that approximate the image intensities inside and outside the contour respectively. The first two terms seek to separate an image into two regions of constant image intensities. This minimization problem is converted into a level-set evolution equation by using a level set formulation. Due to its lack of explicit dependence on gradient or edge information, this model is very well suited to detect objects whose boundaries are not necessarily defined by gradients or with very smooth boundaries. We aim to leverage this property of the Chan-Vese technique to segment blurred out and low-contrast iris images.

D. A Modification

The method described above has proven to be very useful for image segmentation, especially for medical images, deriving its power from explicitly modeling the regions both inside and outside the contour. The above formulation, in addition to assuming that the object of interest has homogeneous statistics, also assumes that the object background has homogeneous statistics as well. However, this is not true in most of the real world images, especially so in the case of iris images (due to eyelids, eyelashes, eyebrows, skin etc). Therefore, the statistics of the background i.e., parts of the eye other than the iris, end up influencing the iris boundary detection more than the iris texture. In [12] Sundaramoorthi et. al. proposed a modification to the Chan-Vese model, defining an adaptive lookout region which depends on the statistics of the current contour. Using the fact that the statistics of the region inside the contour is modeled by a Gaussian distribution, the adaptive lookout region Σ is obtained by dilating the current contour by an amount equal to the variance of the statistics inside the current contour.

$$D = \Delta_{\sigma(I|\Omega)} \Omega \tag{4}$$

$$\sigma^2(I|\Omega) = \frac{\int_{\Omega} \|I - \mu\|^2}{\int_{\Omega} dx} \tag{5}$$

$$\Sigma = D \backslash \Omega \tag{6}$$

where Δ_σ defines a dilation operation by a factor σ, Ω is the current contour and D is the dilated contour. This allows us to locally explore a small region outside the current contour for the pupil/iris boundary, without having to model the complex background in the iris images.

E. Pupil Segmentation

The pupil segmentation algorithm is posed as a energy minimization problem, with the objective to be minimized defined as follows (Chan-Vese with the modified lookout region),

$$\begin{aligned} E(C, \mu, \bar{\mu}, \lambda_1, \lambda_2) &= \int_{D_{in} \backslash \Omega_{in}} |I(x) - \bar{\mu}|^2 dx \\ &+ \lambda_1 \int_{\Omega_{in}} |I(x) - \mu|^2 dx + \lambda_2 \Gamma(C) \end{aligned} \tag{7}$$

where $I(x)$ is the eye image (we are using $I(x)$ instead of $I(x, y)$ for simplicity), C is the current contour, Ω_{in} is the region inside C, Ω_{out} is the region outside C, $D_{in} = \Delta_{\sigma(I|\Omega_{in})} \Omega_{in}$, $\Gamma(C)$ is the regularization term, μ is the mean pixel intensity within the contour, $\bar{\mu}$ is the mean pixel intensity in the lookout region and λ_1 and λ_2 are scalars weighting the different criteria defining the contour energy. We use the output of the eye center detection to initialize a contour for pupil segmentation.

F. Iris Segmentation

Once the pupil is segmented, we initialize a contour just outside the pupil. However, one simply cannot use Eq. 3 since to detect the outer boundary of the iris, we need to exclude the pupil region from within the region enclosed by the current contour, which leads to the following energy formulation for detecting the outer boundary,

$$\begin{aligned} E(C, \mu, \bar{\mu}, \lambda_1, \lambda_2) &= \int_{D_{in} \setminus \Omega_{in}} |I(x) - \bar{\mu}|^2 dx \\ &+ \lambda_1 \int_{\bar{\Omega}_{in}} |I(x) - \mu|^2 dx + \lambda_2 \Gamma(\Omega) \end{aligned} \tag{8}$$

where $\bar{\Omega}_{in} = \Omega_{in} \setminus \Omega_{pupil}$ defines the region inside the current contour C excluding the pupil, Ω_{pupil} is the pupil region found after pupil segmentation and $D_{in} = \Delta_{\sigma(I|\bar{\Omega}_{in})} \Omega_{in}$.

IV. Experimental Results

To evaluate our iris segmentation algorithm, we performed experiments on a subset of the Iris Challenge Evaluation (ICE) [2] and Face and Ocular Challenge Set (FOCS) [1] datasets. The ICE database has iris images obtained from still subjects under very good imaging conditions while the FOCS database has images obtained from moving subjects at a distance under harsh illumination conditions. We selected a subset of 1061 images from the ICE database of 61 subjects for our experiments. The iris images are of a high quality with an average of 200 pixels or more across the iris diameter within an image of size 640×480. The FOCS database on the other hand has 9588 images of 136 subjects. The database is characterized by impairments such as variations in illumination, out-of-focus blur, sensor noise, specular reflections, partially occluded iris and off-angle iris. Further the iris region is very small (about 50 pixels wide) within an image of resolution 750 × 600. See Fig.6 and Fig.7 for some typical images from the ICE and FOCS database respectively.

Since the ICE database has good quality images, we simulate image degradation by simulating out-of-focus images, i.e., starting from images taken with the subject at the focal length of the camera, we simulate images taken away from the focal plane, both towards and away from the camera. With the focal plane at 50cm from the camera, we simulate images of subjects from -9cm to +11cm from the focal plane. See [4] for more details on how the images were simulated. We show iris segmentation results from the proposed method in Fig.8. Notice the significant amount of blurring in the images which degrade the otherwise sharp boundaries between the pupil/iris and iris/sclera boundary. The proposed algorithm by virtue of considering region statistics rather than image gradients is able to segment the iris regions even in the presence of severe blurring. Table. I shows the False Reject Rate(FRR) (@ 1% False Accept Rate(FAR)) of iris matching on these simulated iris images at distance -9cm to 11cm on either side of the focal plane. The images at different distances have different amounts of blurring.

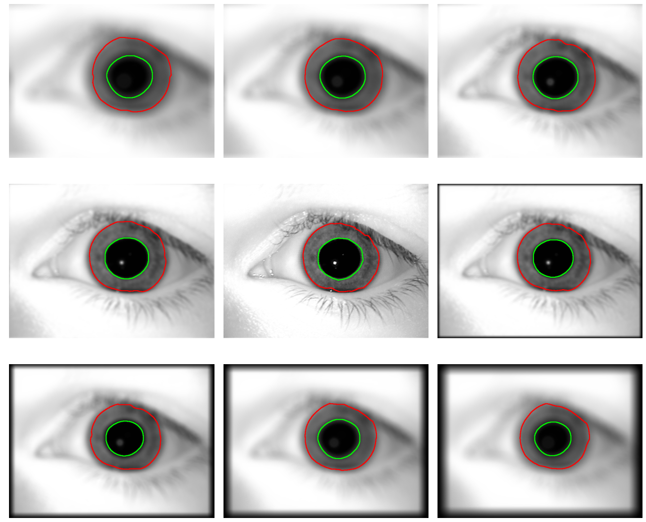

Fig. 8. ICE database segmentation with blurring. See text for more details.

TABLE I
RECOGNITION RESULTS FOR ICE DATABASE

Distance (in cm)	Iriscode (FRR in %)	
	FAR=1%	FAR=0.1%
-9 to 11	13.1	16.4
-7 to 7	1.86	3.12
-5 to 5	1.23	1.74
-3 to 3	1.08	1.42
-1 to 1	0.95	1.21
0	0.70	1.00

We also present results of iris segmentation on a subset of the FOCS database in comparison with other popular iris segmentation methods and iris matching results on the full FOCS database. Fig.9 and Fig.10 shows examples of successful and failed iris segmentations on the FOCS database. In Table.II we present the results (Equal Error Rate and False Reject Rates) of iris matching on the full FOCS database. In Table.III we show the results of comparing the proposed iris segmentation method to other popular iris segmentation methods. Our segmentation method does better than the competing techniques on the challenging FOCS database.

TABLE II
RECOGNITION RESULTS FOR FOCS DATABASE

EER (in %)	Iriscode (FRR in %)	
FAR=FRR	FAR=1%	FAR=0.1%
33.1%	70%	81.3%

TABLE III
SEGMENTATION OF 404 IMAGES IN FOCS DATABASE

Segmentation Technique	Correctly Segmented	Accuracy
Integro-Differential Operator[7]	207	51.2%
Hough Transform	210	52%
Geodesic Active Contours[11]	358	88.6%
Proposed Method	365	90.3%

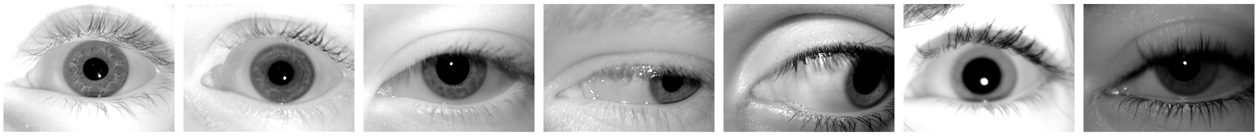

Fig. 6. Typical images from the ICE database.

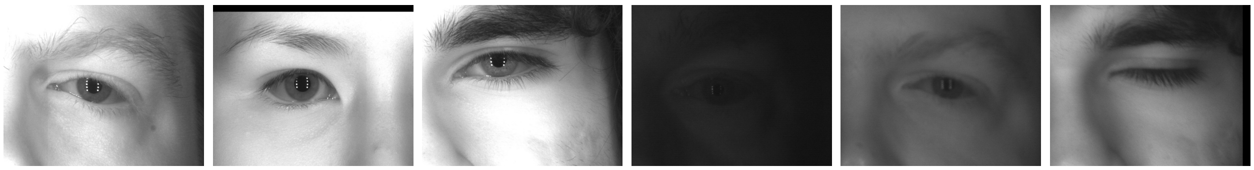

Fig. 7. Typical images from the FOCS database, both good and poor quality images.

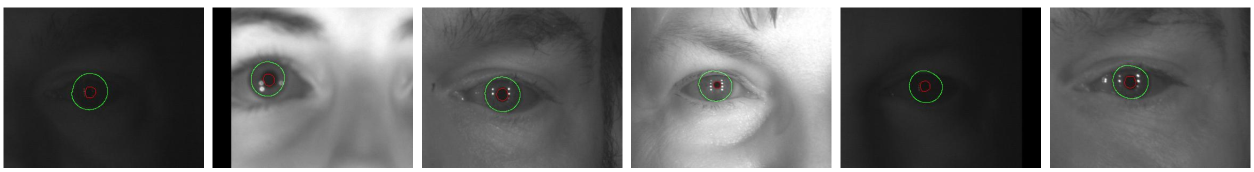

Fig. 9. FOCS Dataset: Iris Segmentation: Successful Cases

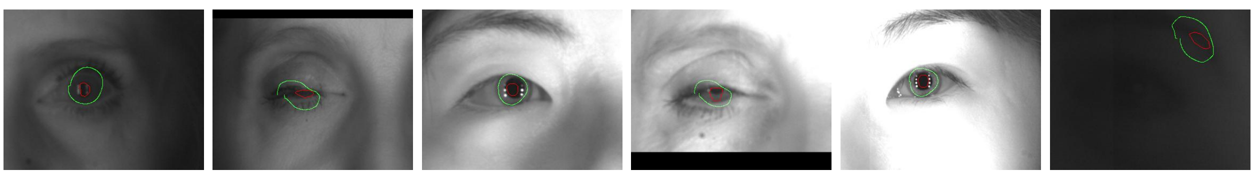

Fig. 10. FOCS Dataset: Iris Segmentation: Failure Cases

V. Conclusion

Recognition of humans from their iris patterns under very harsh imaging conditions is a challenging task. Accurate iris segmentation is the main bottleneck to improved iris recognition under these conditions. In this paper we proposed a region based active contour segmentation algorithm which is more suited to segment iris regions under difficult imaging scenarios. We demonstrated the effective of our approach on the benchmark ICE dataset and the very challenging FOCS dataset.

Acknowledgment

This work is sponsored under IARPA BAA 09-02 through the Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-10-2-0013. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing official policies, either expressed or implied, of IARPA, the Army Research Laboratory, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

References

[1] Face and ocular challenge series (focs) http://www.nist.gov/itl/iad/ig/focs.cfm. 1, 4

[2] Iris challenge evaluation (ice) http://www.nist.gov/itl/iad/ig/ice.cfm. 1, 4

[3] A. Abhyankar and S. Schuckers. Active shape models for effective iris segmentation. In *SPIE*, volume 6202, page 6202, 2006. 1

[4] V. Boddeti and B. Kumar. Extended-depth-of-field iris recognition using unrestored wavefront-coded imagery. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 40(3):495–508, 2010. 1, 4

[5] V. Boddeti, M. Smereka, and B. V. K. V. Kumar. A comparative evaluation of iris and ocular recognition methods on challenging ocular images. In *IJCB*, 2011. 2

[6] T. Chan and L. Vese. Active contours without edges. *Image Processing, IEEE Transactions on*, 10(2):266–277, 2001. 1, 2, 3

[7] J. Daugman. How iris recognition works. *Circuits and Systems for Video Technology, IEEE Transactions on*, 14(1):21–30, 2004. 1, 5

[8] J. Daugman. New methods in iris recognition. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, 37(5):1167–1175, 2007. 1, 2

[9] D. Mumford and J. Shah. Optimal approximations by piecewise smooth functions and associated variational problems. *Communications on pure and applied mathematics*, 42(5):577–685, 1989. 3

[10] H. Proença. Iris recognition: On the segmentation of degraded images acquired in the visible wavelength. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 32(8):1502–1516, 2010. 1

[11] S. Shah and A. Ross. Iris segmentation using geodesic active contours. *Information Forensics and Security, IEEE Transactions on*, 4(4):824–836, 2009. 1, 5

[12] G. Sundaramoorthi, S. Soatto, and A. Yezzi. Curious snakes: A minimum latency solution to the cluttered background problem in active contours. 2010. 2, 3