Image Quality Treatment to Improve Iris Biometric Systems

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Abstract. Currently, there are many solutions related to biometric systems for users authentication purposes based on iris image, because, the human iris characteristics remain unalterable for each individual. In order to improve the iris biometric system accuracy, the images captured need to reach a minimum quality level. However, different distortion can occur in the image acquisition step, such as blurring, affecting the global performance of the system. In this context, this research proposes a methodology to treat the blurred images and to improve their quality. The deblurring process is a complicated task, and most of the methodologies need the Point Spread Function (PSF) to correct the impaired image. A method named blind deconvolution is used in this work to get the PSF value, and then it is used in the deblurring process to improve the image quality. Experimental results demonstrated that corrected images reached minor Hamming Distance values, considering iris images of the same user, improving the biometric system performance. Thus, with the solution proposed, the False no-Match rate parameter of the global system decreased from 27.82% to 4.41%.

Keywords: Biometric System, Image Treatment, Blur Degradation, Iris recognition, Image Quality.

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1 Introduction

Nowadays, user authentication solutions are necessary for many applications, such as, access to information systems, controlled environments, computers and mobile devices [18]. The implementations of those solutions are based on the use of features such as alphanumeric passwords, one-dimensional or two-dimensional code cards and different applications based on biometric recognition. In the specific case of biometrics, it consists in the use of biological characteristics extracted from the human being as mechanisms of identification. There are several manners of using biometrics; the most used are fingerprint, hand geometry, ear geometry, facial recognition, retinal mapping and iris recognition.

Currently, iris recognition is the most reliable between the non-intrusive biometric methods, because the amount of texture information provided that facilitates the authentication task. Also, iris characteristics remain stable during the entire life of an individual [6].The first iris biometric recognition system was introduced by [6] and the proposed iris recognition methodology is composed by the following steps: acquisition, segmentation, normalization, pattern extraction and finally the recognition step, which consists in the verification or validation of the user in the system. The image acquisition plays a very important role in the global process, because if the image presents quality impairments, the next steps will be affected and the accuracy of the system will not be acceptable.

In recent years, there are some works that study the relation between the image quality and the biometric solution performance [8, 1, 12]. For example, in [15], authors propose the use of traditional image quality metrics such as MSE and PSNR to detect a minimum quality level in cases of blurred images. The problem of blurred images is also treated in [9]. In [2] a non-reference image quality assessment is presented to prevent the authentication of fake users.

The image processing research area has grown considerably during the past decade with the increased utilization of image in several applications coupled with improvements in the speed and cost effectiveness of digital computers and related signal processing technologies [16]. Images are obtained in areas ranging from photography to astronomy, remote sensing, medical imaging, among others. In each case, the original image is the ideal representation of the observed scene. However, the observation process is never perfect [3]. The process of image capturing is always susceptible to degradation, such as blur; for instances, in the acquisition step of an iris biometric recognition system.

In this context, the main objective of the present research is to propose a pre-processing step in the iris recognition methodology to improve the quality of blurred iris images. Then, the usefulness of proposed method is validated by comparing the number of authentications using blurred and deblurred iris images of the same subject.

The proposed pre-processing step is based on the determination of Point Spread Function (PSF). Restoring a blurred image without the PSF is a complicated process treated by many research. In this work, in order to achieve the expected results, the following two main problems were identified:

1. Find a metric that determines the image quality index of a blurred image.

2. Determinate the Point Spread Function (PSF) value using the Blind Deconvolution Algorithm.

The metric chosen is an algorithm proposed by Do Quoc Bao and described in [7]. The method uses a single image as input and returns a value between 0 and 1, where 0 represents the best quality and 1 means the worst quality due a high level of blur. The Blind Deconvolution function implemented in MATLAB estimates a PSF value for the degraded image. With these two problems solved, itâs possible to use the quality index value obtained and the PSF value as parameters for a correction method, in this case, the Lucy Deconvolution Algorithm was chosen.

Once the image is treated, it can go through the all iris recognition steps to obtain the Hamming Distance (HD) of both the restored and the reference image. The value of HD determines if an image of the same user is authenticated or not; thus, the objective of this research is to reduce the number of incorrect rejections. The performance of a biometric recognition system is assessed by some parameters, the most used are, the True Match (TM) that indicates the number of correct authentications, the False Match that is related to false authentication (FM) and False No-Match (FNM) that represents the number of genuine users that were rejected, probably, because the low image quality used as input. Then, the FNM parameter is the most appropriate to analyze the results obtained in this work

The remaining of the paper is organized as follows. In Section 2, the research methodology is presented. In Section 3, a brief review of the theoretical fundamentals is presented, they are regarding to biometric recognition systems, blur metric algorithms, deconvolution methods and the processing involved in an iris recognition system. The test methodology and solution proposed is detailed in Section 4. Experimental results are described and discussed in Section 5. Finally, conclusions are outlined in Section 6.

2 Research Methodology

The methodology adopted in this work is the Experimental Research Method, in which the researcher manipulate the variables to determinate their effects on the object of study. In the experimental phase of the project some public data bases of Iris images were analyzed, and since CASIA-Iris-Interval was the most accepted and cited in related works, it was chosen. The original images were impaired with blur, and then, the blurred images were assessed by an image quality metric. The iris software chosen is called OSIRIS (Open Source for Iris), and it is an open source iris recognition system developed in the framework of the BioSecure project [14]. The system has a configure file as input and it processes an amount of listed images to give the Hamming Distance as output. With the results, it will be analyzed how the blur intensity affects the image quality and also the global the iris biometric system performance. Also, the proposed method indicates how the quality image index can be used to restore a blurred image to reach an acceptable image quality value.

3 Theoretical Fundamentals

In this section, a brief review of biometric recognition methods are described. Then, the fundamentals of the blur metric algorithm, the deconvolution method and the iris processing method used by OSIRIS are presented.

3.1 Biometric Recognition Systems

Nowadays, there are different biometric recognition solutions based on human characteristics, such as, hand, fingerprint, face and ear geometry, voice characteristics, retinal mapping, iris recognition, DNA, odor, among others. The performance of these biometric recognition methodologies can be compared by considering the following aspects [10]:

- Universality: determines whether all persons have a human characteristic to be assessed;
- Distinctiveness: it takes into account that the characteristic must be unique to each person;
- Permanence: check if the feature does not change over time;
- Collectability: determines the ease in collecting this feature;
- Performance: is the available resources for the implementation of the recognition process and the time required;
- Acceptability: acceptance of people for the provision of the characteristic;
- Imposture: the possibility of feature imitation; it should be noted that a smaller value of this parameter indicates better performance.

Considering these aspects, Table 1 presents a resume of the comparison between some of the most used biometric technique solutions, such as DNA, ear, face, fingerprint and iris.

Table 1: Comparison of some Biometric Recognition Systems

Feature	Ear	Face	Fingerpr.	Iris
Universality	aver.	high	aver.	high
Distinctiveness	aver.	low	high	high
Permanence	high	aver.	high	high
Data collect	aver.	high	aver.	aver.
Performance	aver.	low	high	high
Acceptability	high	high	aver.	low
Imposture	aver.	high	aver.	low

It can be observed that a biometric system based on iris presents some advantage regarding to the other solutions, specifically because of the high distinctiveness and low imposture characteristics. It is important to note that the acceptability trends to change along the time. At the present iris biometric solutions are being implemented in most popular electronic devices, such as smart phones, then, people will accept without restrictions.

3.2 Blur Metric Algorithm

The algorithm was programed by DO Quoc Bao, which mathematical model is describe in [4]. The general idea of this method is to be independent from any edge detector and to be able to predict any type of blur annoyance. Thus, it is proposed a new approach which is not based on transient characteristics but on the discrimination between different levels of blur perceptible on a picture. In fact, it is observed that there are difficulties to perceive differences between a blurred image and the same re-blurred image. Consequently, this phenomenon to estimate the blur annoyance is used. It is known that the image's sharpness occurs in its gray component, this justifies a blur annoyance estimation based on its luminance component.

Let F denotes luminance component and *m x n* as the size in pixels of an image. To estimate the blur annoyance of F, first we must blur the image in order to get a new blurred image, denoted by B. It is chosen a horizontal and vertical strong low-pass filter denoted by h_y and h_h, then, B_{ver} and B_{hor} are determined as presented in (1).

$$\mathrm{B}_{Ver} = h_v \times F \qquad B_{Hor} = h_h \times F \; (1)$$

$$\mathrm{h}_v = \frac{1}{9} \times [111111111] \;\; h_v^T \; (2)$$

After that, it is necessary to study the variation of the neighbors pixels, thus, the absolute difference images D_F_{Ver}, D_F_{Hor}, D_B_{Ver} and D_B_{hor} are computed using with the following relations:

$$D\_F_{Ver}(i,j) = \text{Abs(F(i,j) - F(i-1, j))} \tag{3}$$

$$D\_B_{Ver}(i,j) = \text{Abs}(B_{Ver}\text{(i,j)} - B_{Ver}\text{(i-1, j))} \tag{4}$$

$$D\_F_{Hor}(i,j) = \text{Abs(F(i,j) - F(i, j-1))} \tag{5}$$

$$D\_B_{Hor}(i,j) = \text{Abs}(B_{Hor}(\text{i,j}) - B_{Hor}(\text{i, j-1})) \quad (6)$$

where i goes from 0 through *m - 1*, and *j* from 1 through *n - 1*.

Once the absolute difference images are obtained, the variation of the neighboring pixels can be calculated. If this value is high, the initial image was sharp, although if it is low means that the original image was already blurred. To calculate this variation, the following equations are used:

$$V_{Ver} = Max(0, D\_F_{Ver}(j,i) - D\_B_{Ver}(i,j)) \quad (7)$$

$$V_{Hor} = Max(0, D\_F_{Hor}(j,i) - D\_B_{Hor}(i,j)) \quad (8)$$

Where i goes from 1 through *m - 1*, and *j* from 1 through *n - 1*.

Then, to compare the variations, the sums of the vertical and horizontal coefficients of both initial and derivate images are calculated as followed:

$$s\_F_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Ver}(i,j) \quad (9)$$

$$s\_V_{Ver} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Ver}(i,j) \quad (10)$$

$$s\_F_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_F_{Hor}(i,j) \quad (11)$$

$$s\_V_{Hor} = \sum_{i,j=1}^{m-1,n-1} D\_V_{Hor}(i,j) \quad (12)$$

where s_F_{ver},s_F_{Hor},s_V_{ver} e s_V_{hor}, represents the sum of the absolute differences.

After that, the result is converted into a scale from 0 to 1:

$$b\_F_{Ver} = \frac{s\_F_{Ver} - s\_V_{Ver}}{s\_F_{Ver}} \quad (13)$$

$$b\_F_{Hor} = \frac{s\_F_{Hor} - s\_V_{Hor}}{s\_F_{Hor}} \quad (14)$$

where b_F_{Ver} and b_F_{Hor} are the results converted in a scale from 0 to 1.

At the end, it is selected the higher blur intensity amount, the vertical or the horizontal one as the final blur value:

$$blur_F = Max(b\_F_{Ver}, b\_F_{Hor}) \quad (15)$$

3.3 Deconvolution Methods

In the proposed solution the Blind and Lucy-Richardson Deconvolution methods are used and explained as follows.

3.3.1 Blind Deconvolution

Blind deconvolution is the problem of recovering a sharp version of an input blurred image when the blur kernel is unknown [11]. The method consists in testing multiple sizes and PSF inputs configured dynamically, and get the one in which the output image has the best quality assessed by the blur metric. Once the PSF value is obtained, it will be used in the Lucy-Richardson algorithm to restore the image considering its best quality.

3.3.2 Lucy-Richardson Deconvolution

Lucy-Richardson algorithm is a method that consists in recovering a latent image which has been blurred with a known point spread function. An image is a huge matrix of numbers known as pixels. The PSF describes the response of an imaging to a point source or point object [19]. A captured image is generally slightly blurred, and this image can be represented mathematically as:

$$\text{H} = \text{W} \times \text{S} \quad (16)$$

where *H* represents the original image, *S* the *Point Spread Function (PSF)* and $*$ denotes the operation of convolution. The basic idea is to calculate the mostly restored image, given a degraded input image *(W)* and a known point spread function *(S)*, and for that we have the following equation [17]:

$$W_{i,r+1} = W_{i,r} \sum_k \frac{S_{i,k} H_k}{\sum_j S_{j,k} W_{j,r}} \quad (17)$$

where i and j represents the location and k the iteration count.

3.4 Processing stages in an Iris Recognizing System

This section describes the different steps of iris recognition system, which was implemented in the OSIRIS solution. After the images are processed and the matching process is performed an output value between 0 and 1 known as Hamming Distance is determined, which is basically the quantification of the difference between the original and tested iris code images.

3.4.1 Segmentation

The segmentation process focuses on finding the precise contours of the iris [13, 7]. The result of this step will be a reference for all of the following steps. The basic idea is to find the inner boundary and the outer boundary; thus, the pixels are classified as iris and not-iris. Fig. 1 presents the original image (a), the image with the borders identified and also considers any noise present in the input image (b), and finally the mask binary file (c).

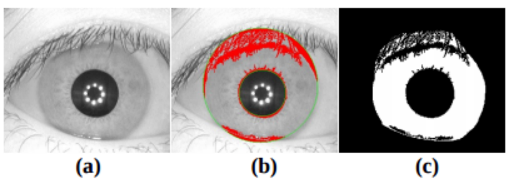

Figure 1: Original image (a), area and noise in the iris (b), output mask (c).

3.4.2 Normalization

The normalization process basically transforms the iris area, which is a circumference, into a size-invariant rectangle using Daugman's Rubber Sheet Model [5], as presented in Fig. 2 (a); the normalized mask (b) is also obtained.

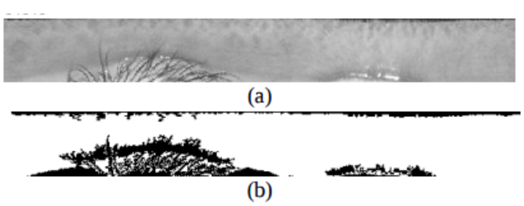

Figure 2: Normalized image (a), normalized mask (b).

3.4.3 Encoding

The encoding step extracts the characteristics using Daugman's method. The general idea it is to quantify irregular pattern in a quadrant of the complex plane in each resultant projected by a Gabor 2D filter. This can be represented by the following equation:

$$h\{\text{Re,Im}\} = sgn_{\{\text{Re,Im}\}} \int_{\rho}\int_{\phi} I(\rho,\phi)\, \mathrm{e}^{-i\omega(\theta_0-\theta)} \quad (18)$$

$$e^{-(r_0-\rho)^2/alpha^2} e^{-(\theta_0-\phi)^2/\beta^2} \rho d\rho d\phi \quad (19)$$

,where h{Re, Im}is a complex bit of imaginary and real parts 0 or 1 (sgn), I(ρ, φ) is the image represented in a polar coordinate system, α and β are the wavelet size parameters, (r_0, θ_0) are the coordinates of each region of the iris for which the phasor coordinates are computed and ω is the wavelet frequency.

Once that all the characteristics are extracted, Osiris will generate a binary image template, presented in Fig. 3, and save it. This code image can be loaded whenever needed for the matching process.

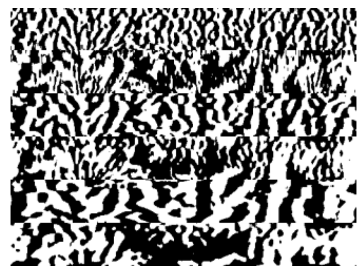

Figure 3: Iris code template (6 Gabor filters).

3.4.4 Matching

In the matching process the Osiris algorithm will load and compare the similarity of two iris code templates. As output we have the HD (Hamming Distance), which is calculated with amount of bits that diverge between the two images. As a final result, we have a score that ranges from 0 through 1, in which 0 means equal and 1 means completely different.

4 Solution Proposed

Fig. 4 introduces a block diagram that represents the test methodology used in the proposed solution to improve the quality score of blurred images.

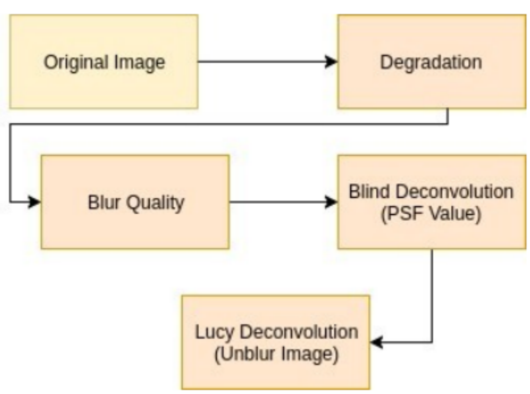

Figure 4: Block Diagram of the test methodology.

Each one of these blocks is explained as follows.

4.1 Reference Image

In this step, an image set is chosen from the CASIA-Iris-Interval data base. Next, the quality algorithm measures the original image quality and saves this value into a local variable; this value is used for comparison proposals with the blurred images.

4.2 Degradation

In this part, blurred images are created from the original using a noise function implemented in MATLAB. The function requires three input parameters: the original image, the type blur, which is a Gaussian function in this case, and the intensity of the noise that uses a range from 1 through 8, where 1 is the lowest blur and 8 the highest one. For each blur value, an output image is generated.

4.3 Blur Quality

As soon as the degradation part is over, the output image is assessed by a Blur Quality measure function, which returns the intensity of the image blur that will be used to in the Lucy Deconvolution Method to restore the image. The Blur Metric method is represented by (15) and the previous depended equations.

4.4 Unblur Quality

This part intends that the blurred imageâs Point Spread Function (PSF) degradation value is not known, and uses the blind deconvolution method to estimate this value. Fig. 5, represents the algorithm used to restore the blurred image.

The dotted region represents a loop in the algorithm. This part will pre-treat the image, using Blind Deconvlution function â represented by the first block, and by comparing the restorations' quality, using the Blur Metric algorithm (represented by the second block), it will return the best PSF value. Once the estimated PSF value is obtained Lucy-Richardson method (3.2.2) will improve the final image quality(fifth block) and return the restored image.

4.5 Iris Biometric System

The last step is to compare the images using OSIRIS. In this part the reference image, the blurred and deblurred images are processed in the system and once all the processing part is done, it is time for the matching step. In this step two comparisons are performed, the reference with the blurred image and the reference with the deblurred image, and that process return the Hamming Distance score of each comparison.

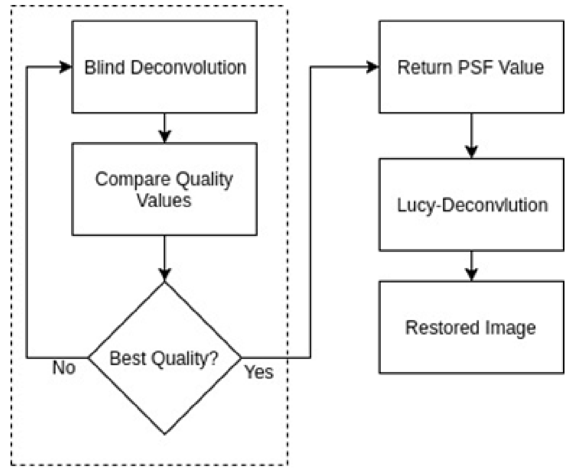

Figure 5: Flowchart of the proposed solution for restoring blurred images.

5 Results

An amount of 102 reference images were chosen randomly from the database, and others 1632 images were created (816 blurred and 816 deblurred). The Fig. 6 presents a specific sample of the reference, blur and deblurred images.

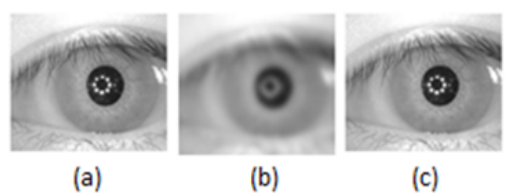

Figure 6: Samples of (a) Reference image, (b) Blurred image and (c) Deblurred image.

Table II presents the original, degraded and restored image quality scores. Note that these results correspond to a sole original image ($Ori\_113\_L\_S1113L07$). In the second column named BLUR, the blur intensity applied in the image is presented, in which blur 1 to 8 are the lowest and highest, respectively. Then the image quality score was calculated in the original (Q. original), blurred (Q. Blur) and deblurred image (Q. Deblur). It can be observed that the deblurring process improve the quality image scores in all the blur quality levels.

In order to understand how the blur affect on the iris recognition system, Table III presents the HD of

Table 2: Quality Indexes of Original, Blurred and Deblurred images of the $Ori\_113\_L\_S1113L07$ image.

Blur	Q. orig.	Q. Blur	Q. Deblur
1	0.3089	0.5061	0.3607
2	0.3089	0.7261	0.4948
3	0.3089	0.8512	0.5766
4	0.3089	0.9137	0.6228
5	0.3089	0.9441	0.6250
6	0.3089	0.9591	0.6373
7	0.3089	0.9678	0.6399
8	0.3089	0.9735	0.6314

Blurred and Deblurred images. It can be observed that the highest blur values generate a HD greater than lower blur intensity. The same reference image present in Table II was chosen because it lets to observe that the HD exceed the limit score for authentication (0.334) in the case of blurred image, but after the deblurring process the new HD is lesser than 0.334.

Table 3: Hamming Distances of Blurred and Deblurred Images of $Ori\_113\_L\_S1113L07$ image.

Blur Intensity	HD blurred image	HD Deblurred image
1	0.1095	0.1467
2	0.1952	0.1803
3	0.2386	0.2361
4	0.2788	0.2831
5	0.2884	0.2668
6	0.3129	0.2830
7	0.3392	0.3159
8	0.3496	0.3089

Comparing the Deblur Quality and the Blur Quality, it is possible to notice that the deblurred image is with a lower value than the blurred ones, and since the Blur Metric algorithm describe that the quality score is near to 0 the image quality is better, it is possible to assume that the deblurred image is better in the most cases. It is also noticeable that the hamming distance is lower in the deblurred image in all cases except for the one with the blur intensity 1, although this value is next to 0.10, which for the matching process is a very good value for a blurred image itself.

Fig. 7 presents the average improvement rate of the deblurred images, using the HD parameter for all the image used as test material. This rate is obtained by (BLUR-DEBLUR)/BLUR. It is noticeable that the rate of improvement in most cases are closer to 10%, which represent an acceptable performance improvement. Only the rate that corresponds to Blur 1 is not depicted because the rate was negative, but, as stated bfore, the HD is closer to 0.10 in all cases, then this blur intensity does not represent a risk in the authentication process.

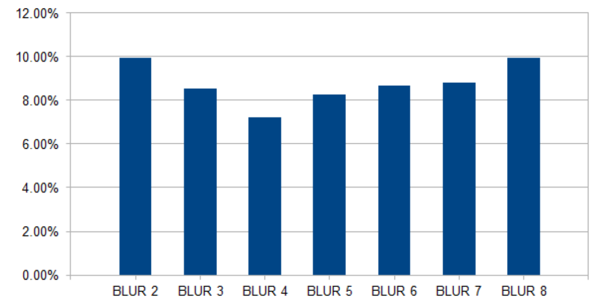

Figure 7: Average Improvement Rate Considering Hamming Distance.

Table IV show the number of images that obtained a HD greater than 0.334 considering the blurred and deblurred images using the 8 blur intensity levels. This indicates the number of FNM for each blur.

Table 4: Number of Genuine Users That Were Rejected for Each Blur Intensity (FNM)

Blur intensity	FNM - Blurred images	FNM - Deblurred images
8	96	19
7	84	13
6	41	4
5	5	0
4	1	0
3	0	0
2	0	0

Finally, Table V presents the results of the iris biometric recognition system performance considering the following two scenarios, using the blurred images created considering the 8 blur intensities, and the deblurred images obtained using the proposed methodology. The parameter used to evaluate the performance is the FNM rate.

Table 5: Global Performance of the Biometric System considering FNM

FNM rate - Blurred image	FNM rate - Deblurred images
27.82%	4.41%

As can be observed from Tables IV and V, the proposed methodology to treat image quality helps to improve the global performance of an iris biometric system.

6 Conclusion

Experimental results show that the HD values obtained by an Iris biometric recognition system is certainly related with the blur intensity, considering images of the same user. Therefore, the global performance of the system depends on the quality of the iris image used as input. The solution proposed improved the quality of iris images, and reduce the HD values. The methodology proposed was very useful to improve the the performance of the system, reducing the FNM rate from 27.82% to 4.41%. The solution proposed was tested in conjunction with the OSIRIS software, but it can be extended to others systems, because the methodology is applied in the input image.

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