Quality Metrics Influence on Iris Recognition Systems Performance

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Abstract - When working with biometrics, regardless of the modality, it is essential to consider data quality, as it can limit the accuracy of recognition systems. In this context, the assessment of biometric samples quality by defining quality metrics can be used to enhance the performance and functionality of a biometric system. In this work, the influence of ISO/IEC 29794-6 quality metrics on iris recognition systems performance has been analysed. To carry out the analysis, the corresponding metrics have been calculated according to the computational method detailed in the standard and a quality score has been obtained. Then, in order to determine the metrics influence, an open source iris recognition system as well as one publicly available dataset, have been used. Results show to what extent an iris recognition system can be affected by input images quality, and also the most influential quality metrics on recognition accuracy.

Index Terms — Biometrics, iris recognition, quality metrics, sample quality

I. INTRODUCTION

There are two main reasons why image quality assessment is of paramount importance when working with automated biometric systems. On the one hand, it affects systems performance, and on the other hand, it is basic to improve interoperability.

It is a fact that poor input data quality adversely impacts biometric systems performance, as it is responsible for error rate increasing and can be a great weakness of certain implementations. There are different ways of reducing the impact of poor data quality, but many of them depend on considering effective methods of automated data quality measurement. This way, in order to enhance biometric systems performance and functionality, the assessment of biometric samples quality by defining quality metrics should be considered.

Regarding interoperability, it is also a fact that there is a lack of interoperability of quality scores, which makes data exchange between systems difficult. Being this the situation, the need of biometric samples quality assessment is clear.

Specifically, in the framework of iris recognition systems, the term quality should not be only associated to the acquisition settings of the sample, such as image resolution or bit depth, but also to image capture from imperfect sources, as occurs for example with subject blinking or gaze deviation, or under non-proper conditions. Currently, a draft version of an international standard exists, aimed to assess the quality of iris images. This standard, named ISO/IEC 29794-6 (Biometric sample quality – Part 6: Iris image) [1], was initiated by Working Group 3 of ISO Subcommittee SC 37 (Biometrics) in January 2009.

In ISO/IEC 29794-6, terms and quantitative methodologies relevant to the characterization and assessment of the quality of iris images used in biometric recognition are defined. More in detail, the current working draft of the standard (SC 37 N4302) defines 19 covariates (10 image acquisition covariates and 9 subject covariates) and 20 quality metrics for assessing the utility of an iris image. Among the 20 quality metrics, 17 are computed from a single image, and 3 are computed from two images. These quality components are quantitative measures of image-specific or subject-specific covariates. Once obtained the quality metrics, in order to indicate the overall image quality, either a vector of quality components or a scalar quality score can be used.

One of the main inconveniences of ISO/IEC 29794-6 is that the performance assessment of specific quality algorithms is out of its scope. Being this the situation, it is fundamental to determine the quality metrics influence on iris recognition systems to enhance their performance and functionality. Such analysis has been carried out in this paper. In order to do it, quality metrics defined in ISO/IEC 29794-6 have been calculated according to the computational method detailed in the standard. In the cases in which no definition is given, an alternative method proposed by authors has been considered. After the computation, a quality score (overall scalar computed from a vector of quality components) has been obtained. This process is explained in detail in Section 2 of the document. After that, to determine the metrics influence, an open source iris recognition system as well as one publicly available dataset, have been used. Both the experiments and the corresponding results are described in Section 3 of the paper. Finally, conclusions and future working lines are provided.

II. IMAGE QUALITY DESCRIPTION AND CALCULATION

In this section of the document, an overview about image quality is provided. After that, all steps followed from the single quality metrics calculation to the quality score obtaining are explained in detail.

A. Quality covariates vs. quality metrics

Part 6 of ISO/IEC 29794 establishes requirements on covariates that affect iris recognition performance. According to the standard, a covariate can be defined as the individual variable or parameter that either directly or when interacting with other covariates affects iris recognition, being the influence measured in terms of error rate. Specifically, 19 covariates have been identified as the most influential on recognition accuracy. Among the 19 quality covariates, 10 of them are related to the design and implementation of the image acquisition equipment and environment (the so-called iris acquisition covariates), and the remaining 9, are related to subject-specific or subject-influenced/controlled factors (the so-called iris subject covariates).

On the one hand, iris acquisition covariates are based on the fixed design parameters of the acquisition device or the operation of the device in accordance with the following requirements:

1. Satisfactory resolution and sharpness.
2. Sufficient contrast in the iris to support information extraction and template generation.
3. Positioning of the subject's iris in the camera's field of view with good focus while minimizing or eliminating impairments, such as specular reflections and optical aberrations.

On the other hand, iris subject covariates can be inherent in each subject, and so, not directly controlled/modifiable by them (e.g. eye colour or intrinsic iris-pupil contrast), but they can also be the result of a controlled action of the subject (e.g. occlusion due to eyelash/eyelid or head rotation).

Apart from the quality covariates, 20 quality metrics are defined in the standard. These quality components are mostly quantitative measures of the image-specific and subject-specific covariates. Among the 20 quality metrics, 17 are computed from a single image, and 3 are computed from two images. In this paper, only the metrics computed from a single image will be analysed, as authors consider that quality metrics computed from two images are more related to matching results and their objective lies in checking the behaviour of the overall recognition system, considering any database, independently of the number or images per user existing.

In Table 1, both iris acquisition and iris subject covariates are indicated, together with the quality metric or metrics that better quantify them. In some cases, no quality metric is applicable to the corresponding covariate. When working with iris acquisition covariates, this occurs when the metrics are not such, but a parameter that depends on the capture device configuration (e.g. distribution of energy across certain wavelength range in the case of *Dedicated illumination* or modulation transfer function of the imaging system in the case of *Optical resolution*). When working with iris subject covariates, the fact that no metric is applicable only happens in the case of *Eye Wear*, as it implies the use of external elements such glasses or lenses. Although the standard does not define any quality metric to quantify this covariate, it is feasible to quantify the effect of potential eyeglasses reflections by calculating *Usable iris area*, as done with *Occlusion due to specular reflections* covariate. Regarding contact lenses, it is not necessary to automatically detect soft contact lenses, as they do not affect iris images. On the contrary, patterned contact lenses, which hide iris tissue, shall be detected and prohibited. Hard contact lenses should be also detected and *Usable iris area* computed to determine if the iris image is affected or not.

TABLE I
IRIS COVARIATES AND CORRESPONDING QUALITY METRICS DEFINED IN ISO/IEC 29794-6 (SC 37 N4302) [1]

	COVARIATE	QUALITY METRIC
IRIS ACQUISITION COVARIATES	Dedicated illumination	*Not applicable*
	Defocus	Sharpness
	Gray scale density	Gray scale utilization
	Motion blur	Motion blur
	Occlusion due to specular reflections	Usable iris area
	Optical distortion	*Not applicable*
	Optical resolution	*Not applicable*
	Pixel aspect ratio	*Not applicable*
	Sensor noise	Signal-to-Noise ratio
	Spatial sampling rate	*Not applicable*
IRIS SUBJECT COVARIATES	Eye colour	Iris-sclera boundary contrast Iris-pupil boundary contrast
	Eye wear	*Not applicable*
	Intrinsic iris-pupil contrast	Iris-pupil boundary contrast
	Intrinsic iris-sclera contrast	Iris-sclera boundary contrast
	Iris shape	Iris boundary shape Pupil boundary shape
	Occlusion due to eyelash/eyelid	Usable iris area
	Off-axis orientation – head rotation	Frontal head rotation - roll
	Off-axis orientation – sight direction	Azimuth frontal gaze Polar frontal gaze
	Pupil size	Pupil to iris ratio

B. Quality metrics calculation

Once known both the iris covariates and the corresponding quality metric(s), the calculation method considered for each of the metrics will be explained.

In Table II, the computational methods defined in ISO/IEC 29794-6 (SC 37 N4302) to calculate the different quality metrics are shown. As it can be observed, there are some metrics for which no computational method is defined yet. In these cases, authors suggest a method, which has been used to carry out the experiments, and which is explained in detail below.

TABLE II
QUALITY METRICS COMPUTATION ACCORDING TO ISO/IEC 29794-6 (SC 37 N4302) [1]

QUALITY METRIC	COMPUTATIONAL METHOD
Frontal gaze - azimuth	*Not defined*
Frontal gaze - polar	*Not defined*
Frontal head rotation – roll	If the entire ocular region is visible in the image, FRONTAL_HEAD_ROTATION shall be computed as the angle measured between the horizontal and the line drawn between the left and right corners of the eye (medial and lateral canthus)
Gray scale utilization	*Not defined*
Iris image authenticity	*Not defined*
Iris boundary shape	IRIS_BOUNDARY_SHAPE should be measured as eccentricity of iris-sclera boundary
Iris-pupil boundary contrast	IRIS_PUPIL_BOUNDARY_CONTRAST shall be computed as the average grey level differences at the iris-pupil boundary locations along a horizontal row of pixels, which include the pupil centre. It shall be the arithmetic mean of differences in grey scale values at the left and right iris-pupil boundaries
Iris-pupil concentricity	IRIS_PUPIL_CONCENTRICITY= $\frac{\sqrt{(X_{pupil}-X_{iris})^2+(Y_{pupil}-Y_{iris})^2}}{IRIS\_RADIUS}$
Iris-sclera boundary contrast	IRIS_SCLERA_BOUNDARY_CONTRAST shall be computed as the average grey level differences at the iris-sclera boundary locations along a horizontal row of pixels, which include the iris centre. It shall be the arithmetic mean of differences in grey scale values at the left and right iris-sclera boundaries
Iris size	IRIS_SIZE = IRIS_RADIUS or IRIS_SIZE = (4 * IRIS_AREA) / IRIS_PERIMETRE if no circularity assumed
Margin	MARGIN = 1 – 0.25 1 – 0.25 * (LEFT_MARGIN_DEFICIENCY + RIGHT_MARGIN_DEFICIENCY + + UP_MARGIN_DEFICIENCY + DOWN_MARGIN_DEFICIENCY) where X_MARGIN_DEFICIENCY = $\left\{\begin{array}{ll} 1 - X\_MARGIN / 0,6 & \text{if } X\_MARGIN < 0,6 \\ 0 & \text{if } X\_MARGIN \geq 0,6 \end{array}\right\}$ being X = LEFT / RIGHT Y_MARGIN_DEFICIENCY = $\left\{\begin{array}{ll} 1 - Y\_MARGIN / 0,2 & \text{if } Y\_MARGIN < 0,2 \\ 0 & \text{if } Y\_MARGIN \geq 0,2 \end{array}\right\}$ being Y = UP / DOWN and LEFT_MARGIN = max {0, X_{IRIS_CENTER} / IRIS_SIZE -1 } RIGHT_MARGIN = max {0, [IMAGE_WIDTH – (X_{IRIS_CENTER} + IRIS_SIZE)] / IRIS_SIZE} UP_MARGIN = max {0, [IMAGE_HEIGHT – (Y_{IRIS_CENTER} + IRIS_SIZE)] / IRIS_SIZE} DOWN_MARGIN = max {0, Y_{IRIS_CENTER} / IRIS_SIZE -1 }
Motion blur	*Not defined*
Pupil boundary shape	PUPIL_BOUNDARY_SHAPE = $\frac{2 \cdot \sqrt{\pi \cdot PUPIL\_AREA}}{PUPIL\_PERIMETRE}$
Pupil to iris ratio	PUPIL_IRIS_RATIO=PUPIL_SIZE/IRIS_SIZE where PUPIL_SIZE calculation is analogous to IRIS_SIZE calculation
Sharpness	According to Daugman's Focus Score [2]
Signal-to-Noise ratio	SIGNAL_TO_NOISE = 0,95 * |maximum(intensityLevel) – minimum(intensityLevel)| where intensityLevel is computed for the iris region only
Usable iris area	*Not defined*

The method proposed by authors to calculate the quality metrics not defined by ISO/IEC 29794-6 (SC 37 N4302) is shown next:

- *Frontal gaze – azimuth and polar*

  According to the standard, FRONTAL_GAZE_AZIMUTH and FRONTAL_GAZE_POLAR estimate the direction of displacement between the optical axis of the eye and the optical axis of the camera, considering the azimuthal and polar angles respectively. In both cases, the measure includes both head angular orientation and eye-gaze angle relative to the head. When this kind of deviation is produced, the pupil and iris boundaries are not circular but elliptical. Specifically, in the azimuthal case, the major axis of the ellipse coincides with or is close to Cartesian axis "Y", and the minor axis coincides with or is close to Cartesian axis "X" (see Figure 1a). On the other hand, in the polar case, the major axis of the ellipse coincides with or is close to Cartesian axis "X", and the minor axis coincides with or is close to Cartesian axis "Y" (see Figure 1b). Being this the situation, authors calculate the azimuthal/polar angle according to the ellipse's foci.

In the case of the ellipse, the eccentricity value is between 0 and 1. When the eccentricity is 0, the foci coincide with the center point and the resulting figure is a circle. As the eccentricity tends toward 1, the ellipse elongates. Considering that the minimum elongation of the ellipse corresponds to an azimuthal/polar angle of 0º, and the maximum corresponds to an azimuthal/polar angle of 90º, the exact azimuthal/polar angle can be directly calculated from the distance between the foci.

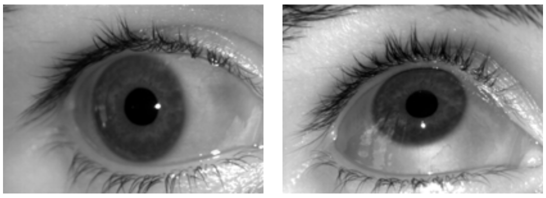

Figure 1. Gaze deviation
(a) azimuthal case and (b) polar case

- *Gray scale utilization*

According to the standard under analysis, GRAY_SCALE_UTILIZATION must check that the overall iris image has a dynamic range of at least 256 grey levels, allocating at least 8-bits with a minimum of 7 bits of useful information (just valid iris portion of the image). An image with a good quality indicates a properly exposed image, with a wide, well distributed spread of intensity values. In order to check if the distribution of intensity values is appropriate, authors have decided to use kurtosis. In statistics and probability theory, kurtosis is defined as a measure of the peakedness of the data. High kurtosis values represent more concentrated data, whereas low values represent more scattered data. In this sense, low kurtosis values are desired to guarantee good GRAY_SCALE_UTILIZATION.

- *Iris image authenticity*

Iris image authenticity shall measure the likelihood that the iris image was captured from a live/real human eye. In this case, authors have decided not to include this metric in the quality analysis for several reasons. First of all, it is difficult and even almost impossible to find public databases of artificial or fake iris images nowadays. Secondly, authors consider that image authenticity is not directly related to image quality, but more with anti-spoofing and liveness detection mechanisms, which is a very wide field. Finally, this metric is still not clearly defined in ISO/IEC 29794-6 (SC 37 N4302). Nevertheless, some alternatives to determine iris image authenticity can be consulted in [3-7].

- *Motion blur*

MOTION_BLUR measures the degree of distortion in the image due to motion. Such motion can occur as a consequence of either the subject relative motion or the camera relative motion during exposure time. In order to express MOTION_BLUR, both the relative magnitude (strength) and the direction (angle) of the image motion have to be calculated. The computation method followed in this case is the one explained in [8]. Since there are two measurable components of motion blur, instead of considering the two different metrics separately, authors have decided to calculate a single value, given higher weight to magnitude, as considered more influential than direction.

- *Usable iris area*

USABLE_IRIS_AREA is the percentage of iris portion of the image that is not occluded by eyelids, eyelashes or specular reflections due to illumination, ambient conditions, eyewear or nearby facial features. In order to calculate this metric, eyelids, eyelashes and reflections are detected and masked and then, the percentage of non-masked iris area related to the total iris area is computed.

After knowing how to compute all quality metrics, it is necessary to determine how to use them in order to determine the iris image quality.

C. *Image quality calculation*

Once calculated all quality metrics, in order to determine the iris image quality from them, two options are possible. On the one hand, it is possible to produce a scalar quality score indicating the overall image quality or, on the other hand, a vector composed of a set of quality metrics can be considered (see Table III).

TABLE III
QUALITY METRICS VECTOR FORMAT

VECTOR POSITION	QUALITY METRIC
1	*Overall quality scalar value*
2	Frontal gaze - azimuth
3	Frontal gaze - polar
4	Frontal head rotation – roll
5	Gray scale utilization
6	Iris image authenticity (*)
7	Iris boundary shape
8	Iris-pupil boundary contrast
9	Iris-pupil concentricity
10	Iris-sclera boundary contrast
11	Iris size
12	Margin
13	Motion blur
14	Pupil boundary shape
15	Pupil to iris ratio
16	Sharpness
17	Signal-to-Noise ratio
18	Usable iris area

(*) *Iris image authenticity* will not be computed (see Section 2.B)

It is clear that a vector of quality components has more information than an overall scalar value. However, the vector itself cannot be directly used to evaluate how input images quality impacts automatic iris recognition systems performance. Being this the situation, it is necessary to map the N-element quality vector to a scalar overall quality value. In order to do that, different techniques (e.g. weighted sum, neural network, SVM, etc.) can be used to combine the metrics and compute a single scalar iris quality score. In this case, authors have decided to consider a weighted sum of the different quality metrics (excluding *Iris image authenticity)*, choosing the weight values according to each metric influence (see Section III – Experiments and results).

In this case, the vector of quality components will be a vector of integers with length 18. According to ISO/IEC 29794-1 (Biometric sample quality – Part 1: Framework) [9], the overall iris quality (first element of the quality vector), shall be in the range [0,100], being 0 the lowest value and 100 the highest value. A value of 255 represents a failed attempt to assign a quality score, either because an error has occurred, or just because the quality component has not been computed. The rest of vector elements shall be coded in one-byte unsigned integer. In order to calculate the weighted sum of the different quality metrics, authors have decided to map also these values in the range [0,100], as done with the overall iris quality value.

III. EXPERIMENTS AND RESULTS

In this section of the document, two main objectives are considered: determining to what extent iris recognition systems performance can be affected by input images quality and determining the most influential quality metrics on iris recognition accuracy.

In order to carry out the experiments, OSIRIS [10] system has been used. OSIRIS (*Open Source for Iris*) is an open source iris recognition system developed in the framework of the BioSecure Network of Excellence. It is inspired by Daugman works [11] and it consists basically of three steps: segmentation, feature extraction and classification. The segmentation part uses the circular Hough transform and an active contour approach to detect the contours of the iris; the feature extraction part uses Gabor filters to obtain the feature vectors and, finally, the classification part is based on Gabor phase demodulation and Hamming distance classification.

All tests have been performed using Iris Challenge Evaluation (ICE) 2005 database [12], a publicly available database developed by the National Institute of Standards and Technology (NIST). The database consists of 2953 grayscale eye images of 132 people, acquired with an LG2200 camera. Each image has a size of 640x480 pixels. The database can be divided into two sub-databases: one for images of the right iris (1425 iris images from 124 people) and another one for images of the left iris (1528 iris image of 120 people). In most cases, images of the right and left irises are acquired at the same time. In this specific case, the right iris photographs of ICE 2005 have been considered. The reason why ICE dataset was chosen is that the performance of OSIRIS reference system (version 2.01) was tested with the right iris in ICE 2005 database. In addition, most of the covariates described in ISO/IEC 29794-6 can be found in this dataset, so evaluating iris recognition performance according to the quality of the dataset images is possible.

A. General analysis

In this section, a general analysis about the quality metrics influence on iris recognition performance is carried out.

In order to determine which quality metrics are the most influential on recognition accuracy, the following process has been followed:

1. For each quality metric, quality values are represented versus intraclass Hamming Distance (HD) considering all ICE images.

The reason why only intraclass HD is considered to carry out the analysis is that it is easier to check how quality affects when considering images of the same user. When comparing images from different users, both quality and differences in the feature vector affect, so it is more difficult to determine which influence is due to quality and which is due to the difference between features.

2. Values are fitted to a straight line by using the method of least squares.

The method of least squares assumes that the best-fit curve of a given type is the curve that has the minimal least square error from a given set of data. The reason why a straight line and not any other higher-order curve is considered to fit data is that the line slope provides all the information needed. When working with recognition systems, it is a fact that the more input images quality, the lower intraclass HD difference between samples. Being this the situation, the tendency of quality metrics values (leaving outliers aside) with respect to intraclass distance is decreasing (see an example of this, considering just one quality metric and one user, in Figure 2). The strength of such tendency can be easily observed by analyzing the best-fit straight line slope.

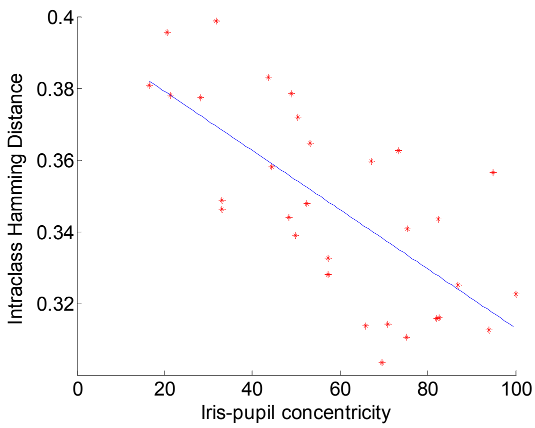

Figure 2. IRIS_PUPIL_CONCENTRICITY vs. intraclass HD for all ICE images of the same user (user ID: 288766)

3. The straight line slopes associated with all quality metrics are compared.

According to the previous point, the quality metrics with the highest slope can be considered the most influential.

After carrying out the abovementioned analysis, the conclusion obtained is that the most influential quality metrics when ICE is used to test OSIRIS are sharpness, motion blur and gaze deviation (either Frontal gaze – azimuth and polar and Frontal head rotation). In all these cases, the decreasing tendency of quality values with respect to intraclass distance was more noticeable than in the case of the rest of metrics. Consequently, the highest weight values were given to these metrics when computing the weighted sum to calculate the single scalar iris quality score. Besides, the least influential quality metrics can be also identified with the proposed analysis method. Such metrics are those in which the variation of quality values with respect to intraclass HD is almost uniform (straight line slope ~ 0). They are Iris and pupil boundary shape and Image margin. The smallest weight values were given to these metrics. Finally, intermediate quality values were given to the quality metrics left.

B. ICE performance

Once identified the influence of the different quality metrics and calculated the overall scalar quality score, the influence of ICE images quality on OSIRIS performance can be determined.

In order to determine the accuracy of a biometric system, error rates have to be measured. There are, among others, two key error rates: false acceptance rate (FAR) and false rejection rate (FRR). When these two rates are equal, the common value is referred to as equal error rate (EER). The lower the equal error rate value, the higher the accuracy of the biometric system. In this paper, the performance of OSIRIS is characterized by FAR, FRR and EER. To evaluate the influence of the quality metrics, three cases have been analysed:

1. Entire dataset used.

   This case is the worst case possible, as all images, regardless of their quality, are considered.

2. Images in which all quality metrics are over the threshold.

   In this second case, apart from the system performance, authors check if the threshold values specified in ISO/IEC 29794-6 (SC 37 N4302) are effective. Threshold values specified in the standard are considered in those cases in which the metric is defined, and threshold values chosen by authors according to the general analysis (previous subsection) are considered otherwise. Once defined all thresholds, only images in which all quality metrics are over the corresponding threshold, are included in the image subset.

3. Images with quality score higher than 0.75.

   The last case is the one in which the overall scalar quality score previously calculated is used. By obtaining the error rates in this case, authors check what happens if not only the minimum quality requirements (defined by the threshold) but something more restrictive is considered.

Based on the results shown in Figure 3, we notice, as expected, a performance increasing trend: as quality of the data increases so does performance. As observed, the worse EER is obtained in the case in which the whole database is used. Once some minimum quality requirements are considered, the EER value improves. The best EER value is obtained in the case in which the quality requirements are the most restrictive.

Though predictable in some sense, the results obtained in this paper are quite interesting, because with the quality score obtained, it is possible to select images which can achieve a desired level of performance. Taking such images as a reference, it would be also possible to determine the quality characteristics that the input images of an iris recognition system with specific performance constraints should have.

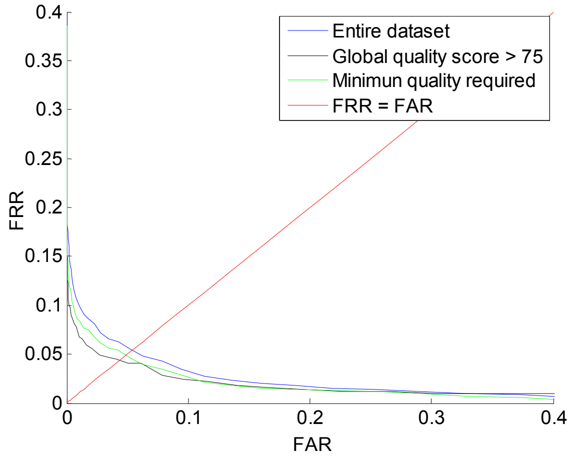

Figure 3. OSIRIS performance considering different quality requirements of ICE input images

IV. CONCLUSIONS

In this paper, the influence of ISO/IEC 29794-6 (SC 37 N4302) quality metrics on OSIRIS iris recognition system performance has been analysed. To carry out the analysis, the corresponding metrics have been calculated according to the computational method detailed in the standard and a quality score has been obtained. Then, in order to determine the metrics influence, OSIRIS recognition system and ICE dataset, both publicly available, have been used.

Apart from analysing the current Working Draft version of ISO/IEC 29794-6, something very useful in terms of the Standard development, results show to what extent an iris recognition system can be affected by input images quality. Besides, the most (and also the least) influential quality metrics on recognition accuracy have been identified. Sharpness, motion blur and gaze deviation have been confirmed as the most influential factors, so special care must be taken regarding this parameters when capturing iris samples.

Another important fact to mention is that with the quality score obtained, it is possible to select images which can achieve a desired level of performance. Taking such images as a reference, it would be possible to determine the quality characteristics that the input images of an iris recognition system with specific performance constraints should have.

Finally, although a good analysis of 29794-6 (SC 37 N4302) has been done in this paper, it is important to consider that this version of the standard is only a Working Draft. For this reason, not all quality metrics are defined and potential methods to compute the non-defined quality metrics had to be proposed by authors. Being this the situation, the standard under study has to evolve until being definitive, and so, a similar analysis, or even more exhaustive, will have to be done in the future, once a more stable version appears.

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VI. VITA

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