# Face to Iris Area Ratio as a Feature for Children Detection in Digital Forensics Applications

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***Abstract*—This paper presents a new geometrical feature based on iris geometry for automatic children detection in digital images. The proposed feature is based on simple geometrical measures of face elements and especially iris. Iris outer boundary is approximated as a circle and the proposed feature is defined using the iris area and the distance of iris from mouth line. This approach is compared with two similar geometrical features. Experimental results show the superiority of the proposed feature over the existing ones. The proposed feature is more robust compared to the existing features that use geometrical information from human faces and gives better classification results, useful to digital forensics applications.**

***Keywords—iris; face detection; digital forensics; child sexual abuse; child pornography;***

## I. Introduction

Automatic children detection in digital images or videos is a task that can find several applications in situations where special attention to children has to be given, such as access limitation, targeted marketing, image analysis and retrieval or digital forensics. This paper focuses in digital forensics since child sexual abuse (CSA) content in digital images or videos is a worldwide growing problem due to ease of access and reputed anonymity of internet. Nowadays, child pornographic images and videos are produced and distributed with an alarmingly increasing rate. Advanced countries legislation determines the possession or distribution of child sexual abuse material as a crime [1].

In parallel, nowadays personal computers have increased storage capacity and lower price, something that allows the storage of a huge amount of digital images and videos. Thus, the efficient identification of child sexual abuse material in countless digital files of images or hours of videos is a very demanding task. In many cases law enforcement units have to complete this task manually. And time is also a crucial parameter since prosecutors have usually time limits to decide over prosecution or custody of a suspect. So, automatic detection of CSA content in image or video files would be an essential support to law enforcement. Image processing algorithms can provide skin/nudity detection, face detection, eyes, nose or mouth localization, face size estimation and even texture information that can be combined to create useful features. Recent approaches towards this scope can be found in the literature and are briefly presented in the next section.

The human eye iris is a unique biometric characteristic that have been proposed for person identification. Moreover, the corneal diameter, also known as horizontal visible iris diameter (HVID), slightly grows from newborns to adults. The horizontal diameter of the cornea on average is 10 *mm* in infants and 11 *mm* in adults [2]. This 10% increase of HVID compared with the e.g. 40%-50% increase of the head circumference from newborns to adults [3] provides a significant biometric difference in the development of head geometry, which can be used by algorithms to separate children from adults.

This paper examines three geometrical features based on elements of faces that can be used for the detection of children in digital images. Features are based on measures of the iris area, the distance between irises, the distance of iris from mouth and an estimation of face area. All the necessary data are quite easy to be derived from digital images by using known algorithms and provide better robustness. Experiments that have been applied on a small but demanding sample of images have shown that the use of the proposed Face to Iris Area Ratio (FIAR) provide a feature with superior results compared to existing geometrical features.

In Section II the literature review is presented. The proposed Face to Iris Area Ratio feature and other two similar features used for comparison are described in section III. Experiments description and results follow in section IV and conclusions are drawn in section V.

## II. Related Work

A simple method to detect images with CSA material is the use of file hashes like MD5 sums. A database with hashes of illegal files is kept updated by law authorities and every record is compared with the files under examination. This method works only with known illegal material and it is easy to be overcome by the simplest change of the file. A similar idea with the same drawbacks scans network traffic to identify known CSA material [4].

Moreover, pornographic material detection methods based on filename association have been proposed in [5,6]. That is, suspicious filenames found in storage media are determined as possible pornographic content. The approaches of [5,6] have the advantage of rapidly assessing a large number of files, however, since the actual content of each file is not assessed, the actual pornographic content may not be determined efficiently.

Content based analysis of images, provide the advantage of searching and classifying previously unknown material and it is difficult to be overcome. Pornographic material detection is a parallel task in CSA content detection. Numerous techniques have been proposed in the literature for the detection of nudity in images. Most of them are based on skin detection [7-12]. Other use visual words or histogram features [10,13].

Many techniques have been proposed for age classification from facial images [14,15] by using geometrical features, texture or color information and combinations of them [6,13, 14,16,17]. Focusing in geometrical features, three distances between facial components are used in [14]: the distance between the eyes, the distance from eyes to mouth and the distance from eyes to nose. In this case the iris area is not taken into account. Moreover, in [17] the geometrical features used include: the iris area, the distance between irises and the width of the face detector result. In this case, the iris area is taken into account but is compared with two distances that measure only the increase of the horizontal dimension of a human face.

In all these techniques face and more specifically eyes, nose, mouth localization is considered as a necessary but challenging preliminary task. During the last three decades, numerous techniques have been developed to attain face or face elements detection [18-20]. More recent techniques address factors such as environmental conditions, facial expression variations, occlusion etc. to improve the performance under specific conditions [21-25].

In this paper we propose a new feature that combines geometrical information from human face including the iris size that slightly changes over the years from newborn to adults and both the human face horizontal and vertical changes. This feature is described in the following section.

## III. Face To Iris Area Ratio

In the following the proposed feature is described in detail. The geometrical information that is used to define the feature is shown in Fig. 1 and consist of: the two iris centers ($C_L$ and $C_R$), the mouth horizontal line estimation ($l_m$) and the horizontal visible iris diameter (HVID) for the two irises which can be easily calculated from the intersection points (*A*, *B*, *C* and *D*) of the line defined from the two iris centers $l_i$ and the two circles that enclose irises.

Based on above points and lines shown in Fig. 1, we calculate HVID as the distance between A and B points or C and D points. We define the distance between iris centers $C_L$ and $C_R$ as $d_i$ and the distances between each iris center $C_L$ and $C_R$ and mouth line $l_m$ as $d_L$ and $d_R$ respectively. Usually $d_L$ and $d_R$ should be equal and their average value $d_m$ is used for the experiments.

Moreover, the area of each iris can be calculated from the points *A*, *B* and *C*, *D* respectively. Usually these areas should be equal and their average value $A_i$ is used for the experiments. Finally, a trapezoid is defined from the iris centers and the intersections of the vertical lines from iris centers to the mouth line. The area of this usually orthogonal shape is used as a normalized estimation of face area and is symbolized as $A_f$. This estimation is more robust than total face estimation, since it does not depend on hair style, beard, baldness, hats, caps or other accessories that usually affect the efficiency of face area detection algorithms.

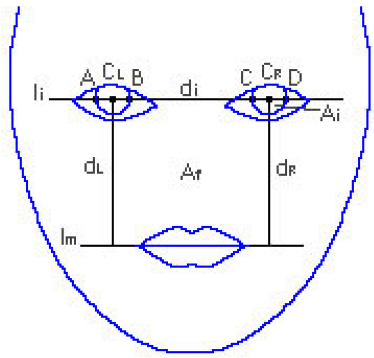



Fig. 1. Geometrical information from face used to define the three features.

So, the three features that will be compared in the experiment section are:

- The Face to Iris Size Ratio defined as $d_i$/HVID, where $d_i$ is the distance between iris centers and HVID the horizontal visible iris diameter. This feature was proposed in [17] and will be symbolized in this paper as FISR.
- The Face Horizontal to Vertical Distance Ratio $d_i/d_m$, where $d_i$ is the distance between iris centers and $d_m$ the average value of the distances from iris centers to the mouth line. This feature was proposed in [14] and will be symbolized in this paper as FHVDR.
- The new Face to Iris Area Ratio (FIAR) defined as sqrt($A_f/A_i$), where $A_f$ is the area of the trapezoid defined from the iris centers and the intersections of the vertical lines from iris centers to the mouth line and $A_i$ is the average value of iris areas.

Although there are a lot of proposed techniques to detect faces and eyes and mouth in faces, we selected to manually detect them, because the purpose of this paper is to test the new feature over the existing ones and this has to be done under ideal situations irrespective of the selected face and eyes detection algorithm. In this way, the results of the presented analysis do not depend on errors of the detection algorithms. Another advantage of the manual procedure is the creation of a ground truth that will be used for testing detection algorithms under real conditions in future work.

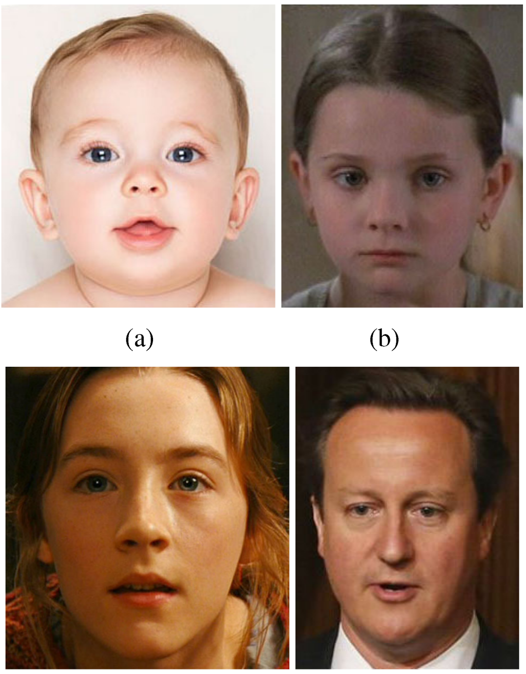
## IV. Experiments And Results

### A. Database

Unfortunately there is not a standard database used to test child detection algorithms. Although there are a lot of available face databases most of them does not contain children in a significant degree. Besides, most of them are unusable for the purpose of children detection test since they do not contain ground truth age information.

So, to examine the efficiency of the proposed features, a new database was created using public images found in the internet with age information. The database consists of 75 images containing faces of people with known age. Age is divided in 4 categories. Fourteen (14) of the people were infants less than 6 years old. Twenty four (24) were children from 6 to 12 years old. Twenty two (22) were teenagers from 12 to 18 years old and the rest fifteen (15) were adults greater than 18 years old. All images were manually processed for the detection of the necessary geometrical information (irises centers, HVIDs and mouth line).

Figure 2 shows four examples of images from the database, one from every category.



(a) (b) (c) (d)

Fig. 2. Examples of images from the database. (a) infant, (b) child at the age of 9, (c) teenager at the age of 14, (d) adult.

### B. Results

Table I presents the values of the three feature ratios (FISR, FHVDR and FIAR) for the four specific images shown in Fig.2. The first column of the results (FISR) shows the Face to Iris Size Ratio which corresponds to the distance between the eyes divided by the iris corneal diameter. This ratio should be greater as we grow from newborns, since irises are moving farther while their size remains more or less the same.

TABLE I. Results of Feature Ratios For Four Specific Images

| **Image** | **Feature Ratios** | | |
|---|---|---|---|
| | ***FISR*** | ***FHVDR*** | ***FIAR*** |
| Infant in Fig. 2a | 4.189 | 1.101 | 4.418 |
| Child in Fig. 2b | 4.579 | 1.012 | 5.079 |
| Teenager in Fig. 2c | 4.405 | 0.851 | 5.389 |
| Adult in Fig. 2d | 5.167 | 0.879 | 6.218 |

The second column of the results (FHVDR) shows the Face Horizontal to Vertical Distance Ratio, which should be smaller as we grow from newborns, since the human skull tends to become more oblong.

The third column of the results (FIAR) shows the proposed feature of Face to Iris Area Ratio. This ratio is greater as we grow from newborns, since face area expands towards both directions while iris area remains more or less constant. Even from these few results it is evident that the proposed FIAR feature is much more robust, since only these values change as foreseen.

Table II presents statistical information of the three features (FISR, FHVDR, FIAR) results per age category. Values for the average, the standard deviation and the coefficient of variation for every category are presented. Differences in averages per category combined with standard deviation values shows the ability for correct classification. The coefficient of variation is independent of the value of average and shows the robustness of the feature. Smaller values of FIAR in most categories show the better robustness of the proposed feature.

TABLE II. Results of Feature Ratios per Age Category

| **Age Category** | **Statistic Measure** | **Feature Ratios** | | |
|---|---|---|---|---|
| | | ***FISR*** | ***FHVDR*** | ***FIAR*** |
| Infants | Average | 3.99 | 1.07 | 4.34 |
| | Standard deviation | 0.23 | 0.07 | 0.25 |
| | Coefficient of variation | 5.86 % | 6.50 % | **5.80** % |
| Children | Average | 4.46 | 0.98 | 5.10 |
| | Standard deviation | 0.26 | 0.07 | 0.28 |
| | Coefficient of variation | 6.03 % | 7.67 % | **5.46** % |
| Teenagers | Average | 4.73 | 0.96 | 5.47 |
| | Standard deviation | 0.24 | 0.07 | 0.25 |
| | Coefficient of variation | 5.08 % | 7.73 % | **4.66** % |
| Adults | Average | 5.22 | 0.92 | 6.15 |
| | Standard deviation | 0.26 | 0.05 | 0.43 |
| | Coefficient of variation | **5.02** % | 5.56 % | 7.06 % |

In order to measure the correct and missing classifications three thresholds were defined for every feature, by using the simplest way, i.e. as the mean value of the averages of two successive categories. By using this simple thresholding the results of misclassifications are presented in Table III. Notice that infants can be misclassified only to older categories and adults only to younger categories, where children and teenagers can be misclassified towards both directions.

TABLE III. MISCLASSIFICATIONS RESULTS PER AGE CATEGORY

| Age Category | Missed as ... | Feature Ratios | | |
|---|---|---|---|---|
| | | *FISR* | *FHVDR* | *FIAR* |
| Infants | older | 21.4 % | 42.9 % | **7.1** % |
| Children | younger | 25.0 % | 20.8 % | **16.7** % |
| | older | 29.2 % | 45.8 % | **16.7** % |
| Teenagers | younger | 27.3 % | 50.0 % | **22.7** % |
| | older | 18.2 % | 40.9 % | **4.5** % |
| Adults | younger | **20.0** % | 33.3 % | 26.7 % |
| **Total** | older + younger | 38.7 % | 62.7 % | **25.3** % |

The smaller misclassification values of the proposed FIAR feature in most age categories and in total, shows the better performance of this feature for classification in age categories.

By using different thresholds we can manage classifications very useful for digital forensics investigators. For example, if the threshold between teenagers and adults is set to an extreme value in order to guarantee that none of teenagers, children or infants be misclassified as adults, the adults correct classification rate is 67% by using FIAR, much greater than the 40% of FISR and the 13% of FHVDR. This means that 67% of the images containing faces could be automatically skipped from manual forensics analysis, considerably decreasing the needed time.

## V. CONCLUSIONS

The necessity of manual effort is the major problem in digital forensics analysis for evidences of children sexual abuse in digital images or videos. This paper proposes a new feature that can be used for age classification in digital images, in order to separate adults from underage. The proposed Face to Iris Area Ratio (FIAR) feature is based on the fact that iris size remains almost constant during childhood, when during the same years horizontal and vertical size of face changes considerably. FIAR feature was compared with two similar geometrical features recently proposed in the literature. Experimental results have shown that FIAR is more robust and gives better classification results. Moreover, it gives the ability to be configured and used in several digital forensics applications.

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