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Assessing the Quality of Acquired Images to Improve Ear Recognition for Children

Abstract. The use of biometrics to secure the identity of children is a continuous research worldwide. In the recent past, it has been realized that one of the promising biometrics is the shape of the ear, especially for children. This is because most of their biometrics change as they grow. However, there are shortcomings involved when using ear recognition in children, usually caused by the surrounding environment, and children can be at times uncooperative, such as moving during image acquisition. Consequently, the quality of acquired images might be affected by issues such as partial imaging, blurriness, sharpness, and illumination. Therefore, in this paper, a method of image quality assessment is proposed. This method detects whether the images are affected by partial imaging, blurriness, sharpness, or illumination. This method assesses the quality of the image to improve ear recognition for children. In this paper, four different test experiments were performed using the AIM database, IIT DELHI ear database, and ear images collected by Council for Scientific and Industrial Research (CSIR) researchers. The Gabor filter and Scale Invariant Feature Transform (SIFT) feature comparison methods were used to assess the quality of images. The experimental results showed that partial ear imaging has less than 16, resulting in low identification accuracy. Meanwhile, blurriness and sharpness were measured using the sharpness value of the image. Therefore, if the sharpness value is below 13, it means that the image is blurry. On the other hand, if the sharpness value is greater than 110, the image quality affects the extracted features and reduces the identification accuracy. Furthermore, it was discovered that the level of illumination in the image varies, the higher the illumination effect, such as the value above 100 affects the features and reduces the identification rate. The overall experimental evaluations demonstrated that image quality assessment is critical in improving ear recognition accuracy.

Keywords: Ear; Recognition; Image Quality; Biometrics; Security; Children.

1 Introduction

The problem of identity theft can be defined as the illegal use of someone's identity, which can be an ID number, identity details, birth certificate, social security number in the case of a child, and more [1]. This problem has been and is still affecting all age groups, from newborns to old people [2]. Therefore, it is important to determine and implement solutions to this problem and to close any identifiable gaps. Over the past few years, there has been a huge gap in protecting the identity of children. This is because not much has been done in the field of biometrics for children. From the research carried out by UNICEF, a conclusion was reached that approximately 230 million children between the ages of 1 and 5 years do not have identification, causing those affected by this issue to be denied education, healthcare, political and economic rights [1].

Biometrics could be defined as a method to use one's unique physical and behavioral characteristics to identify or verify them. This includes fingerprint, hand geometry, retinal, iris, facial, and voice recognition systems. The applications of these systems include airport security, law enforcement, mobile access and authentication, banking, home assistants, building access, schools, public transport, blood banks, border control, voting systems, and more. However, most existing biometric recognition systems have been developed for use by adults, and thus, there is minimal research conducted in the field of biometric recognition systems for children. The major challenge is that children undergo mental and physical development as they grow. The research in [3, 4] agreed that most existing systems designed for adults do not work perfectly for identifying children. It is through meticulous investigation and development of biometric systems for children that we can solve current identification complications. These complications include wrong identification of newborns in hospitals, and the inability to identify missing and illegally adopted children.

The literature has recently proposed different biometric methods for recognizing children, such as face recognition, iris recognition, fingerprint recognition, and footprint recognition [3]. There is, however, one major problem: young children, such as infants, are often uncooperative and do not comprehend or follow instructions, making these solutions or methods unsuitable. For example, using iris as a biometric recognition for children has its challenges [5]. This is because iris capture will be initiated by the child looking directly at the acquisition device. Despite this, newborns, especially premature children, are unable to direct their eyes into a scanning device because they rarely open their eyes. Further, stretching their eyelids to collect an image could be harmful to their eyes. Although the research in [6] pointed out that the iris can be used in children over the age of 2 years. With respect to fingerprints and footprints, a child must touch or hold the acquisition device to capture their fingerprints. For a newborn, this can be a labor-intensive and unhygienic act. Furthermore, children's faces change as they grow, making it difficult for face recognition systems to recognize them [7]. For the most accurate identification of children, ear images are the best biometric method. Compared to other forms of biometrics, obtaining an ear image is quicker, more hygienic, convenient, and less expensive. The use of ear recognition as a solution enables ear images to be captured even while a child is sleeping, eating, or playing using a stand-alone camera or smartphone. Moreover, the size of the ear is larger than other biometric traits including iris, fingerprint, and footprint. This makes it possible to take images with a reasonable degree of distance from the subject.

However, the challenge of using ear recognition systems for infant identification is that the quality of the ear image is affected by a variety of factors. Blurriness, sharpness, illumination, and occlusion are the major factors to consider. If these factors are not normalized, the accuracy of the system will decrease during enrollment, verification, and identification. This may lead to high false-rejection rates. Thus, this paper proposes a method to assess the quality of the captured ear image by detecting the mentioned factors and then normalizing them based on predefined set values. The main objective is to enhance the recognition of the ear in children by assessing the quality of the image.

The remainder of this paper is structured as follows. Section II presents a review of the literature to briefly summarize what others have done to improve ear recognition for children. Section III presents the methodology for how image quality assessment is performed. Section IV presents and discusses the results of the proposed quality assessment technique. Section V concludes the paper and provides future work.

2 Related Works

The identification of children using ear recognition has been explored in numerous studies in recent years. Nevertheless, none of the studies has attempted to assess the quality of the ear images before they are further processed. This list includes patents, conference proceedings, journal articles, and more.

The research in [8] developed a contact-based device called Donut and the amHealth app to identify children based on the shape of their ears. It was developed to optimize the performance of the capture process through image stabilization. The application standardizes the distance, angle, rotation, and lighting of the image. The experiment was carried out by capturing images of 194 participants to assess identification rates. They captured images of the left ear of all participants with and without the Donut and applied the amHealth App algorithm to process the images. To find the most likely matches, they measured the top one and the top ten. As a result of using the Donut, the top one identification rate and top ten identification rate were 99.5 and 99.5%, respectively, in comparison to 38.4 and 24.1%, respectively, without it. Nevertheless, their work is not suitable for use on children when it comes to COVID-19 protocols, and using the device when a child is not asleep will be difficult because the image could be affected by partial imaging and blurriness.

Research in [9] developed a neural network model to analyze ear images collected under unconfined conditions. Sharpness, blurring, and illumination were all factors that affected the images. The model was constructed by analyzing annotated images of ears taken from a database containing landmarks from the ears. The database contained 2058 unconfined labeled images of the ear taken from 231 subjects, which were used to verify and/or recognize the ear. Following extensive comparisons and experiments, the study's results established that both holistic and patch-based AAMs were successful in aligning ear images uploaded to the in-the-wild database. Although ear verification and recognition improve regularly with alignment, the proposed database proved exceedingly difficult to use. The fact that these images were collected from adults offers some encouragement about the alignment issue. However, it does not address the issue of partial imaging or deformed ears of infants and minors under age 18.

To resolve blurriness and illumination changes, the research in [10] used the Random Sample Consensus (RANSAC) normalization technique. Using this technique, the transformation estimation is determined, and average ears are calculated for ear templates and segmentation masks. The implementation of the method was carried out using the Annotated Web Ears (AWE) dataset. By summing and averaging all pixels of each image, which is annotated as perfectly aligned, the average ear is obtained. Therefore, the roll, pitch, and yaw axes are close to zero degrees and are not blocked or contained by accessories. As a result of the experiments, the proposed method, combined with the masking of ear areas, significantly improves the recognition of head pitch variations in ear images. However, this method does not solve the problem of partial ear imaging, i.e., if more than one ear image is affected by quality factors, this will affect recognition, resulting in a higher rate of ear recognition errors.

As a result of realizing that authentication and identification are major challenges in various organizations, researchers designed an efficient fingerprint recognition system [12]. Image enhancement is performed on the fingerprints of infants and toddlers in the proposed system. To determine fingerprint codes, it uses the improved Gabor filter as a preprocessor on the enhanced images. To authenticate and verify the finger codes, the Euclidean distance is then used to match them to test fingerprints. Using existing CMBD and NITG fingerprint datasets, the proposed system was evaluated for efficiency and performance. Despite this, we argue that using ear recognition for infants and toddlers is the most effective way to solve the problem. In this case, the main problem is that children are often uncooperative.

The research in [13] presented a survey on biometric recognition systems for infants and toddlers. Through extensive research, the authors realized that biometric recognition systems for infants and toddlers have many challenges. Some of these challenges include issues like database collection, changes over time in biometrics such as the face, and parents' unwillingness to provide details about their ward. They presented a detailed review of different biometrics and their challenges, especially for infants and toddlers. They claim that to this day the efficiency of biometric algorithms for infants and toddlers is not up to the mark and has to travel a long path to reach the mark. In-depth research is required to evaluate the efficiency of the biometric recognition system for infants and toddlers.

Meanwhile, the research in [14] conducted a comprehensive survey on ear recognition databases, performance evaluation parameters, and existing ear recognition techniques. The authors also developed a new database called NITJEW. The images of NITJEW were captured in an unconstrained environment. The developed database was compared with six existing ear detection and recognition databases. To measure the performance of ear detection and recognition, the authors modified deep learning models, Faster-RCNN and VGG-19. However, their main concern was to evaluate existing biometric systems, and thus not so much was done in terms of experimental evaluations.

3 System Design and Architecture

As shown in Fig. 1, ear recognition involves capturing an image, detecting the ear, extracting, and storing features as well as performing comparisons. The proposed approach includes an image quality assessment stage, as illustrated in Fig. 1.

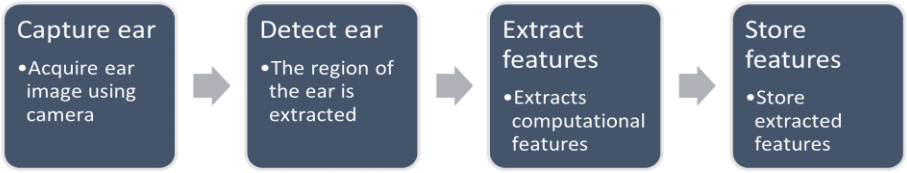

Fig. 1. Traditional ear recognition approaches.

To assess the quality of an image, two types of approaches can be used: subjective and objective. In subjective approaches, judging image quality by data is performed manually by the human, while in objective approaches, identifying and predicting perception of quality is done via computational methods. In this work, the objective approach is used to evaluate four aspects of image quality that affect accuracy for ear recognition, namely: partial ear region, blurriness, sharpness, and illumination.

A partial ear region refers to the captured image that shows part of the ear region, and other ear regions that are not visible because of occlusion or incomplete capture of the image. In most situations, partial images are obtained when the ear image is obscured by clothing or hair, or if the ear detection software only detected a small area of the ear. Image blurriness is a common problem when processing images, which results in an image with reduced edge content and smooth transitions. When an image is being acquired, this can be obtained if a child moves faster or if an acquisition device moves faster. Image sharpness of an image, on the other hand, determines the amount of details in the image that emerges during the acquisition process. Meanwhile, image illumination can be defined as the effect caused by the environment, in this case, by light, on the captured object such as the ear, etc.

Fig. 2. Proposed ear recognition approach.

This proposed model determines the partial region of the ear before determining other factors, which are determined in parallel using the results of the previous evaluation as illustrated in Fig. 2 and Fig. 3.

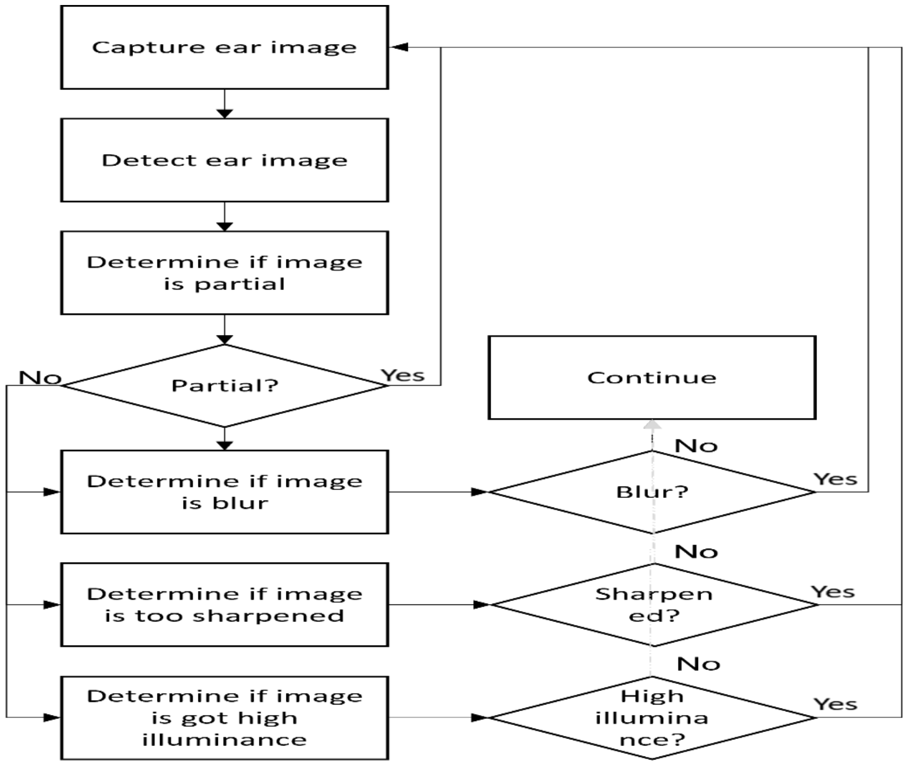

Fig. 3. The proposed ear recognition flow.

3.1 Partial Ear Region

The Scale-Invariant Feature Transform (SIFT) is used to determine whether the acquired image is partial or not. SIFT is a method that is commonly used in image processing to detect and extract features. There are two stages involved in SIFT method, Difference of Gaussian (DoG) and Key-points Detection, as explained in [15].

The SIFT function used in this study returns N number of key points detected from the image. If the number of key points is less than or equal to 16, it means that the image is partial. This indicates that the user is supposed to recapture the image of the ear. Then the proposed image quality assessment method will automatically take the user to the image acquisition stage. This threshold value of 16, was determined experimentally. As part of her Ph.D. in Computer Science program, Esther Gonzalez created the AMI Ear Database. Ear images from the AMI Ear database were cropped into smaller portions and tested to see how many SIFT points can be detected from partial images. On average, 16 or fewer points were detected regardless of the size of the image. The full and partial ear images with detected SIFT key points indicated are illustrated in Fig. 4.

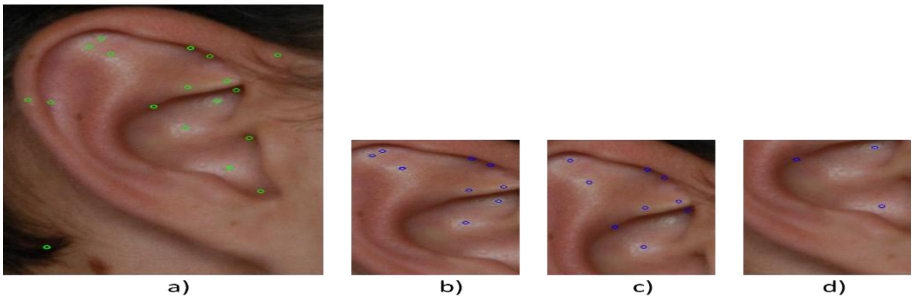

Fig. 4. Illustration of partial ear image, a) full image, b) to c) partial images with 22, 9, 8, and 3 key-point, respectively.

3.2 Image Blurriness and Sharpness

Blurriness and sharpness of the captured images were measured by calculating the level of sharpness in the image using the Laplacian Filter, the algorithm proposed and thoroughly discussed in [16] and [17]. To determine the values of acceptable blurriness and sharpness by the system, images from the IMA database were used to generate blurred images, as shown in Fig. 5. The level of sharpness was then estimated. The higher the sharpness value, the lower the presence of blurriness in the image.

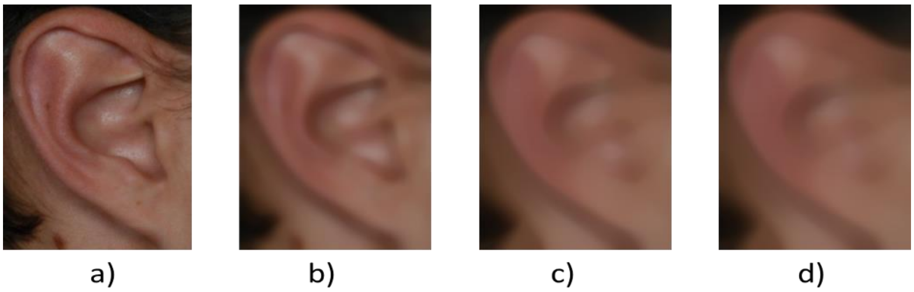

Fig. 5. Image blurriness and sharpness, a) normal image from AIM, b) to d) blurred images with 13.66, 1.56, 1.27, 1.23 detected sharpness values.

3.3 Image Illumination

To detect the level of illumination in the image, a method was used to determine the average amount of illuminance in the image. The method calculates the intensity of each pixel and the nearby pixels. The method used was proposed in [18]. The higher the level of illumination effect, the higher the illuminance value. Illumination is important in the ear image so that the features can be clear. Consequently, too high, and too low of an illuminance value could result in failure to extract features. The thresholds that were determined during experiments include Low Illuminance Threshold (LIT) and High Illuminance Threshold (HIT). Ear images with different illumination effects from the Newborns database and the IIT Delhi ear database were used to test the developed function. Fig. 6 illustrates the images with different illuminance values according to the evaluation.

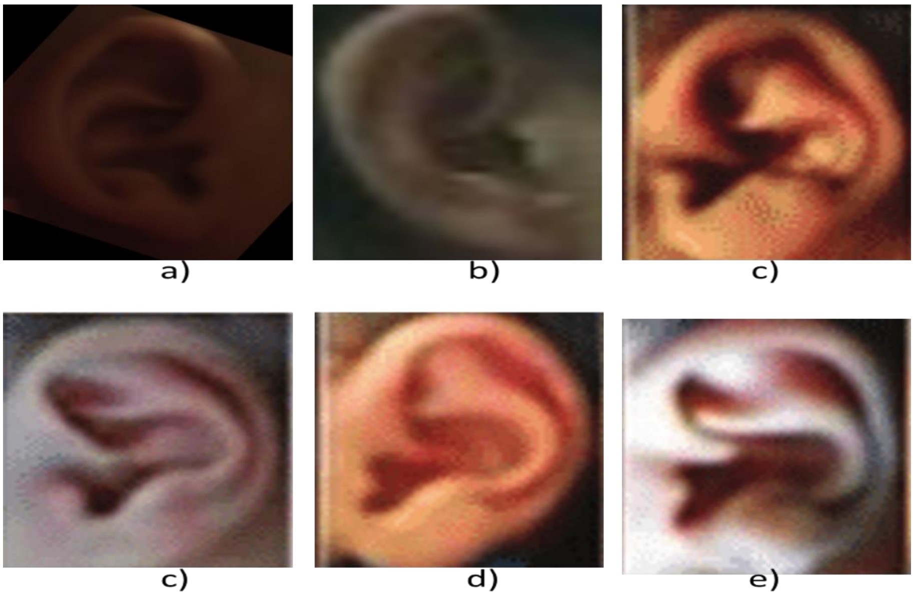

Fig. 6. Detected illuminance value from ear images, a) 24, b) 64, c) 94, d) 104, e) 114, f) 131.

4 Results Analysis and Discussions

To test the proposed image assessment model, four different tests were performed. These included partial ear, blurriness, sharpness, and illumination. The data that was used was collected by the CSIR research [19].

4.1 Partial-ear images testing

A partial image test was performed on 50 images from the AIM database. To determine whether the given images are partial or not, each image was cropped into 10 different ear regions and then passed through the partial detection method. The partial images were grouped into 11 groups for the number of key points: 6, 12, 16, 20, 23, 25, 30, 35, 40, 45, and 50. To verify the accuracy of the match, partial images were compared to the original image using the Gabor and SIFT ear comparison methods.

4.2 Blur and Sharpen ear images testing

From the AIM database, 25 images were selected for testing to determine the blurriness and sharpness of the proposed methods. By applying OpenCV Gaussian and Median blurring methods to each image, three blurred images were generated. Accordingly, the first, second, and third sets of images were all blurred using kernel sizes of 21, 31, and 51. In addition, ten images that looked sharper were selected from the database that the CSIR researchers collected from clinics and schools. For calculating the sharpness of the images, all the images were passed through the function. Thereafter, different sharpness levels were assigned to the images: 1, 4, 6, 8, 10, 14, 18, 40, 80, 100, 120, 150, 200, and 300. A comparison of the generated and selected images with the original image was performed using the Gabor and SIFT ear comparison techniques.

4.3 Images with illumination testing

To test the illumination detection method, a set of data was collected from various sources. These sources included the AIM database, the IIT Delhi ear database, and the CSIR child database. A total of 110 images with different illumination effects were selected. For each selected image, three different images of the same ear were generated. The total number of images then ended up being 330. These images were then passed to the function for calculating the illumination value. Furthermore, the images were grouped based on the illumination value determined: 10, 20, 40, 60, 70, 80, 90, 110, 120, 130, and 140. To determine the matching accuracy, the images were compared with the original images using the Gabor and SIFT methods.

4.4 Results and discussion

To measure the effectiveness of image quality assessment, an ear comparison was performed, as illustrated in Fig. 3. The original images were compared with the image affected by the partial images, blurriness, sharpness, and illumination. To perform ear comparison, the Gabor feature comparison and SIFT feature comparison methods were used. These methods are publicly available in the OpenCV toolbox. The implementation of the proposed model was carried out in C++ with an open CV library. The results are presented in Fig. 7, Fig. 8, and Fig. 9.

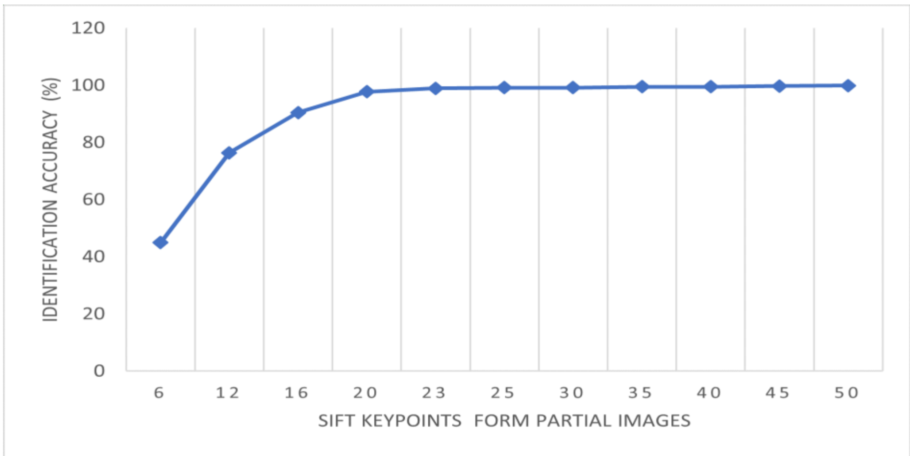

Fig. 7. Accuracy vs. number of sifting key points.

Fig. 7 shows that the accuracy of ear recognition depends on the number of key points detected in the images. The fewer the key points, the lower the recognition accuracy. The higher the number of key points, the greater the details in the images, and consequently the greater the correctness of the resulting recognition.

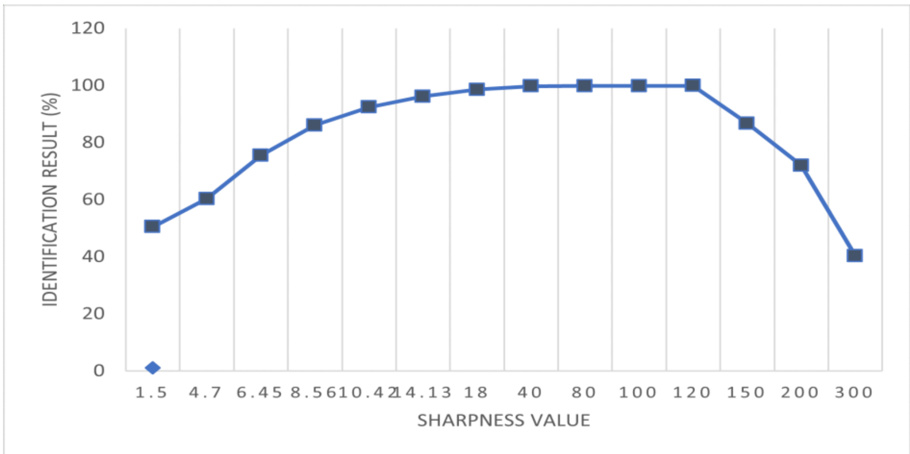

Fig. 8. Accuracy vs. sharpness value.

Fig. 8 presents two effects: blurriness and sharpness. Sharpness is low if the value of sharpness is less than 10, and the result is blurry and inaccurate. This is because the edges of the images that represent the shape are not visible. In contrast, accuracy decreases as the sharpness value increase above 120. The reason for this is that high-sharpened images present too many details, creating a false image of the feature.

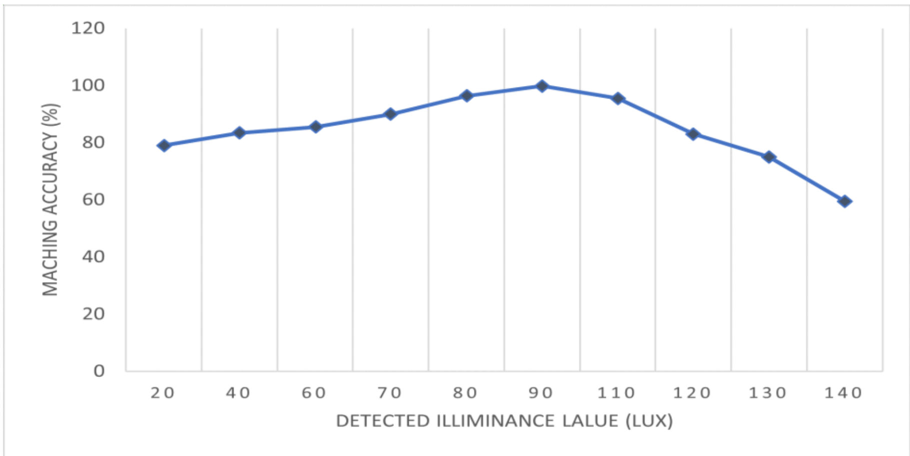

Fig. 9. Accuracy vs. detected image illuminance.

Fig. 9 illustrates the effect of high illumination, in that the higher the illuminance value detected, the lower the recognition accuracy. Similarly, an illuminance of less than 50 affects the quality of the image, as some elements of the image cannot be detected accurately. Consequently, an ear image with an illuminance value between 50 and 100 improves recognition accuracy.

5 Conclusion

This paper presented a method for assessing the quality of an image by looking at four image quality factors, namely partial imaging, blurriness, sharpness, and illumination. From experimental evaluations, it has been proven that performing image quality assessments on ear images can improve the accuracy of ear recognition for children. The novelty of this work lies in normalizing the presence of these factors in captured ear images to reduce recognition errors. Experiments have shown that ear recognition can be improved to identify and verify children using the proposed image quality assessment method. Empirical tests were conducted to determine the acceptable number of key points, a sharpness value, and an illuminance value for captured ear images that can produce a higher ear recognition accuracy. These tests were carried out using data from the AIM and IIT DELHI ear database. Furthermore, data was also collected by CSIR researchers. In the future, the proposed method will have to be applied in a real-time environment, such as in hospitals, to further perform usability testing.

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