The comparison of ear recognition methods under different illumination effects and geometrical

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***Abstract* — This paper presents the study of the permanence of the ear shape. The focus is on comparing ear recognition methods using images affected by illumination and geometrical changes. The main aim of the study is to determine the permanence of the ear shape and when does the ear stop developing. Whereas, the current stage aims to determine the most suitable method that can be used for ear recognition of young children that still under-go different geometrical changes and skin complexion changes. The suitable algorithm should be less sensitive to illumination and more sensitive to growth in order to be able to track significant changes of the ear caused by growth.**

Methods that are evaluated are the Histogram of Oriented Gradients (HOG), Patterns of Oriented Edge Map (POEM), Local Binary Patterns (LBP) and Gabor Filters. These methods were selected theoretically from the literature review as they were reported to show sensitivity to illumination and to geometrical changes. To perform the evaluation, 1000 ear images were generated from 100 ear images, 10 per each subject. For each subject, all 10 images have different illumination and another 10 have different geometrical changes. The results obtained show that a combination of HOG and LBP is suitable for ear recognition under geometrical and illumination changes.

Keywords—ear recognition, illumination, geometrical changes, sensitivity

I. Introduction

The problem of identity theft can be defined as illegal usage of someone's identity, which can be ID number, credential details and birth certificate [1]. These problems affect all age groups from new-borns up to old age people [2]. Therefore, it is important to determine solutions to this problem and close any identifiable gaps as there is still a huge gap in protecting identity of children [3]. The main challenge is that young children under-go lots of development stages after birth, and biometric traits captured at birth may be different as they grow older. Such development includes changes in biometrics and skin colour complexion. Some babies when they are born are very small and rated as under-weight [4]. Additionally, when some babies are born, their skin colour is either lighter or darker compared to the skin colour they maintain as they grow [5].

The outer ear is one of the promising solutions that can be used as a biometric to identify and/or verify the identity of a person [6]-[7]. The outer ear is the visible part of the ear that is located outside of the head. Due to the non-invasive, contactless nature of acquisition and stability of the shape, the ear has potential as a biometric modality of the recognition of children from birth to adulthood [8].

According to medical literature, the ear grows proportionally in all directions during the first four months of birth and after that it slowly increases in size [9]. However, due to gravity the growth of the ear may be elongated in the vertical direction which is visible around the ear lobe [10], see Fig. 1. The rate of elongation is approximately five times greater in the period from four months to the age of eight years, compared to the first 4 months of life [11]. After the age of 8, it remains constant until around 70 years, then it again increases in size towards the ear lobe [11].

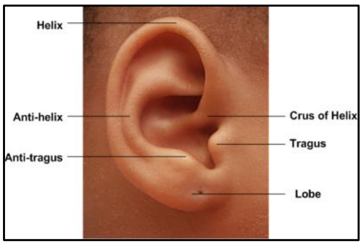

Fig. 1 An image of the outer ear [12]

However, these theories differ for new-borns. It has been observed that ears of new-borns, as well as other physical features of a baby, may be distorted by the position they were in while inside the womb [13]. This is because when babies are born, they are not fully developed. The thick cartilage that gives firm shape to ears is also not yet fully developed. It happens in most cases for new-borns to come out with temporarily folded or otherwise misshapen ears, as shown in Fig. 2. Some parents prefer to unfold their baby ears by consulting qualified doctors, however, the ear may stretch automatically as the child grows [14].

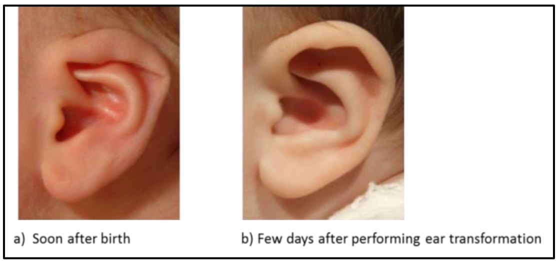

Fig. 2 Folded ear Image of a new-born [13].

One of the first uses of ear recognition as a biometric recognition of children was in 1960 by Fields *et al.* [15]. They compared and analysed images of 206 new-borns manually and concluded that it is possible to identify new-borns apart using the shape of their ears. After that report, there was no much work performed on ear recognition of children for several decades. However, there has recently been an increase on the interest in this field. This includes works done by Tiwari *et al.* [16]-[17] who developed a computationally effective and attractive solution to recognize new-borns automatically by using ears of 210 subjects and achieved accuracy of 89.28%.

However, there are no studies that have been done to evaluate if the ear captured on a new-born can still be used at a later stage to verify the same child. Therefore, in this report we have performed a comparison of four well-known ear recognition algorithms to determine the best method that outperforms other methods if the images of a same person are effect by illumination and geometrical changes. The purpose of this work is to determine if the ear taken soon after birth can be used to identify a child at a later age. This is achieved by determining the permanence of the ear shape and when does the ear stop developing. In addition, this work will assist researchers and scientist in selecting the best method that will give accurate recognition results when ear recognition is used for recognizing children.

The remainder of this paper is presented as follows. Section II presents the related works on existing ear recognition methods. Section III presents the experimental design performed in this study, which includes how ear images used were generated. Section IV represents results and discussion, and conclusion is given in Section V.

II. RELATED WORKS

In this section, reported are existing works based on image recognition and illumination in the field of biometrics. In 2011 Struc *et al.* [18] presented an overview of the mostly used and efficient normalization techniques for solving the problem of illumination variation of face images at the pre-processing level. Struc *et al.* [18] categorised these techniques in to three groups, namely:

- The pre-processing level,
- The feature extraction level, or
- The modelling and/or classification level.

The pre-processing level defined as the process of rendering face images for the purpose of eliminating the effect of illumination. The feature extraction level is used to determine features of the ear that can be used to determine the similarity between two images under different illumination conditions. Authors in [18] recommended algorithms which are less sensitive to the influence of illumination, such as algorithms based on:

- edge maps, i.e. patterns of oriented edge magnitudes [19],
- gradient-based features, i.e. histogram of oriented gradients [20],
- local binary patterns [21] or,
- Gabor wavelet based features [22].

The last group focuses on achieving illumination invariance at the modelling level. Where the techniques for compensating the illumination changes are linked to the type of face model or classification technique employed in the face recognition system.

In 2016 another similar research was performed by El-Naggar *et al.* [23]. Authors classified the characteristics of ear features used by humans and those used by machines for recognition. Features were classified into three categories, namely:

Level one features - these features are ear size, ear skin colour, ear type such as: short and broad, short and narrow, long and narrow or long and broad, earlobe type such as: attached or free and ear shape such as: round, oval, triangular or rectangular. These features are used for recognition as intensity based representation derived by intensity based methods such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [23].
Level two features – these features are said to represent the uniqueness of ears among individuals, which depends on the structure of the ear that consist of curvatures, edges, and how it folds. These features are used for ear recognition as local descriptor methods, such as

- histograms of oriented gradients[20],
- local binary patterns [21],
- Gabor filters [22],
- wavelet transformation [24], and
- scale invariant feature transform (SIFT)[25].

Level three features - these features are detailed observations of unstructured micro ear characteristics which can also provide additional information for ear-based identification. These features include but are not limited to moles, birth marks and piercing [23]. There has been little works reported for recognition on this level of features, which usually involves observation by humans.

In 2016, Tiwari *et al.* [26] investigated adult and infant ear images for automated identification using 2D ear images. The aim of their work was to demonstrate that the ear can be used to recognise infants. Authors performed this investigation by comparing seven ear recognition algorithms and presented the comparison results on a database of adults and infants. The algorithms selected are well-known, namely: Principal Component Analysis (PCA), Independent Component Analysis (ICA), Fisher Linear Discriminant Analysis (FLDA), Geometrical Feature Extraction (GF), Wavelets first proposed by Alfred Haar (Haar), Local Binary Patterns (LBP), and Scale Invariant Feature Transform (SIFT) [26][27]. Tiwari *et al.* further grouped these algorithms into, appearance based (PCA, ICA, and FLDA), geometric based (GF and HAAR) and texture based algorithms (LBP and SIFT). They have concluded that ear can be used as a biometric for recognition of infants. In addition, the results obtained showed that texture based algorithms outperforms other algorithms with maximum accuracy of 92.63% on adult and 90.13% on their infant database [26].

In 2018, Hansley *et al.* [28] proposed a new method for fusion three different description and matching schemes based on: holistic image features, handcrafted (based on image properties) features, and learned features. For holistic features, the PCA method was applied; the results showed that PCA is highly affected by variations in pose and illumination. Hansley *et al.* selected the best performing state-of-the-art handcrafted features for ear recognition, namely: LBP, Binarized statistical image features (BSIF), local phase quantization features (LPQ), rotation invariant LPQs (RILPQ), patterns of oriented edge magnitudes (POEM), histograms of oriented gradients (HOG), dense scale-invariant feature transform (DSIFT) and Gabor wavelets [28].

The results obtained by Hansley *et al.* [28] shows that the performance of handcrafted descriptors degraded when using ear images from uncontrolled environment. Therefore, authors combined convolutional neural networks (CNNs) to improve performance of classification and comparisons, to learn more about the images, and to learn how to describe them in a more discriminative and concise way. The fusion of learned and handcrafted matchers appeared to be complementary as it showed better performance over all the experiments. Furthermore, it was observed that the combination of CNN and HOG was the best performing method for images affected by illumination [28].

In 2018 Emersic *et al.* [29] performed a comprehensive evaluation and analysis of ear recognition models in terms of performance, complexity and resource requirements. Methods that were tested are LBPs, RILPQ and LPQ, binarized statistical image features (BSIF), HOGs, the Dense Scale-Invariant Feature Transform (DSIFT), Gabor wavelets, and POEM. Three different deep-learning models were considered for analysis, which cover some of the most popular architectures for recognition networks from the literature, i.e., ResNet, SqueezeNet (SNet) and the VGG network [29]. The results showed that among the descriptor-based methods DSIF, LPQ and RILPQ the performance is lesser when compared to the other methods, which all performed similarly. In terms of robustness, the POEM-based approach seemed to be stable than the other descriptor techniques. Nevertheless, the deep-learning-based model, SNet was the top performer and also the most robust among the CNN-based approaches.

Besides, in terms of time and space complexity Emersic *et al.* [29] presented that the tested methods differ significantly. Moreover, in situations where resources are scarce, descriptor-based methods may perform better than CNN models.

According to the literature reviewed and to our understanding there has been no work on addressing geometrical changes. Current works focusses on addressing the challenges of illumination and pose variation, for the recognition of both adults and infants. Therefore, the contributions of this work are to determine a framework that is insensitive to illumination and to geometrical changes. These changes are experienced during the early development years of children. As such, we investigated algorithms which should be able to provide accurate results, under conditions where the ear images are affected by variations in illumination. Furthermore, to show a relationship between the growth of the ear and the similarity score, according to geometrical changes.

III. Experimental Design

In this study, mathematically deformed images were used as a substitute for naturally deformed ones due to the difficulties in obtaining longitudinal data on young children. However, authors are currently in a process of acquiring data and as future works we will re-evaluate these results once sufficient longitudinal data is obtained. Similarly, to obtain illumination changes, lighting was adjusted mathematically on images.

A. Experimental Setup

In this study, we have developed two types of experimental setups, where the first setup is based on evaluating the illumination effects and the second setup is based on evaluating geometrical changes. Conclusions are drawn from the results of both experiments according to the aim of the study. Initially, 100 subject images were captured and each image was used to generate 9 images in different illumination effect using the GIMP application. While for different geometrical changes, algorithm by Vass *et al*. [30] was used to generate 9 other images. The geometrical changes were performed by applying lens distortion as it has been observed that in most cases the inner shape of the ear is not highly affected by the geometrical changes compared to the outer shape.

Shown in Fig. 4 and Fig. 5 are examples of generated images from the reference image in Fig. 3. In this example, the ear image was captured from a 2 month old baby.

Fig. 3 Original captured ear image

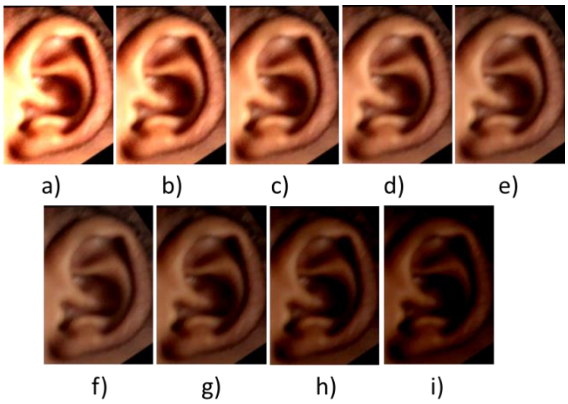

Fig. 4 Ear images with different illumination changes

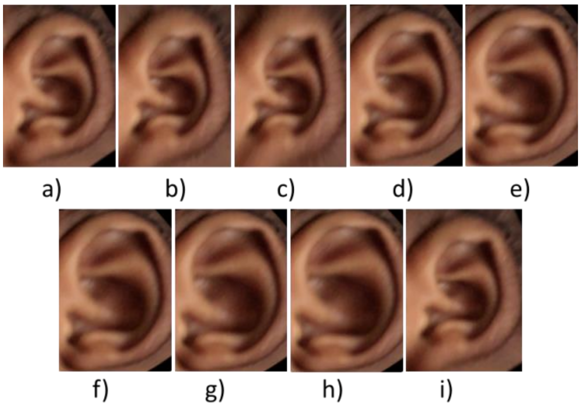

Fig. 5 Ear images with different geometrical changes

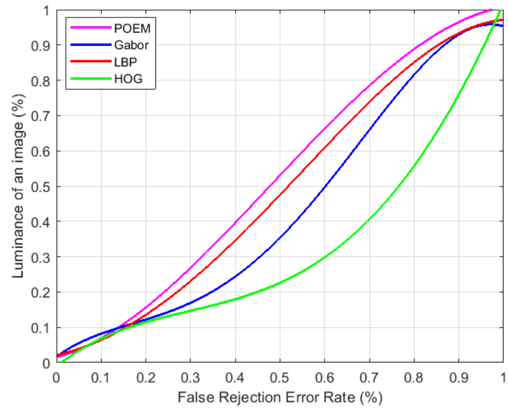

Fig. 6 Sensitivity of evaluated algorithms in terms of illumination

B. Evaluated methods

The selection of the algorithms that are used for evaluation depends on the fact that we are looking at the algorithms that will be suitable for recognising children. The selected methods are Histograms of oriented gradients (HOG) [20], Local binary patterns (LBP) [21], Gabor filters (Gabor wavelet based features) [31], and Patterns of oriented edge magnitudes (POEM) [19]. We have selected these methods because they have been presented as less effective methods when it comes to illumination effect and they fall under level two features as explained in the literature, by Struc *et al*. [18] and El-Naggar *et al.* [23].

IV. Results and Discussion

A. Results

During the experiments, ear features were extracted from all images in the created dataset using all four algorithms, HOG, LBP, POEM and Gabor. Similarity scores were computed using distance based evaluation. The sensitivity to both illumination and geometrical changes was measured based on the behavior of the similarity score as the light and geometry of the image changes. In addition, the evaluation of the results is based on the fact that, the smaller the similarity score, means the more similar are the images resulted in that similarity score. The higher the similarity score means that compared images are different from each other.

The comparison of algorithms was measured using the False Rejection Rate (FRR). FRR is the probability that is computed when the method rejects ear images of the same subject due to illumination or geometrical changes. This probability is mainly derived from the ratio of the number of false rejections divided by the number of verification attempts.

1) Illumination changes

Shown in Fig. *8* are the results obtained when comparing ear images of the same subjects under varying illumination conditions. It can be observed that the best performer between these methods is the HOG method since it gives smaller similarity score as the effect of illumination changes. Gabor method and other two methods also show less sensitivity to the illumination changes, however not as much as the HOG method.

2) Geometrical changes

Shown in Fig. *7* are the results obtained when comparing ear images of the same subjects with different geometrical changes. In this experiment the aim was to determine the method which is more sensitive to geometrical changes. This means that the algorithm should be able to show significant changes in similarity score as the geometry of the image changes. It can be observed that the most sensitive method is the POEM since it gives high similarity score as the effect of geometry changes, followed by the LBP, HOG and Gabor methods.

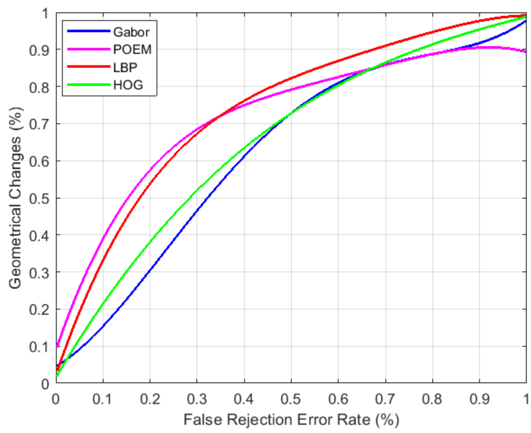

Fig. 7 Sensitivity of evaluated algorithms in terms of geometrical changes.

B. Discussion

The relationship between compared methods is shown in Fig. *8* which corresponds to results presented in Fig. *8* and Fig. *7*. The FRR values obtained under illuminance changes for HOG, Gabor, LBP and POEM are 0.08, 0.15, 0.30 and 0.38, respectively. The FRR values obtained under geometrical changes for HOG, Gabor, LBP and POEM are 0.20, 0.18, 0.39 and 0.45, respectively.

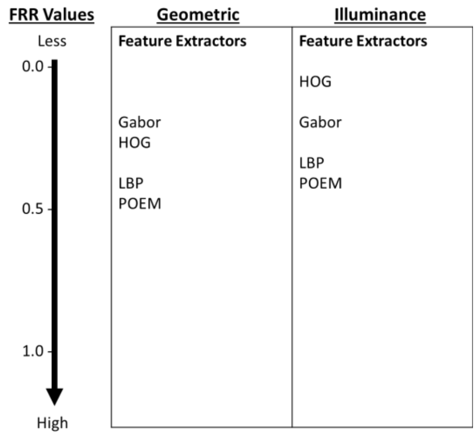

Fig. 8 Results obtained using all four methods on different geometrical and illumination changes

The results show that Gabor filter methods are the least sensitive in both geometric and illumination changes, with FRR of 0.15 and 0.18, respectively, when compared to other methods. However, according to the aim of the study, required algorithm should be less sensitive to illumination and more sensitive to geometric changes. As shown in Fig. 6 middle algorithms are selected, namely, HOG and LBP. Resulted FRR values are 0.08 and 0.30 for illumination changes, and 0.20 and 0.39 for geometrical changes. These algorithms are more sensitive to geometric change, then again are less sensitive to illumination. The experimental results showing that even if there is a geometric change in the ear image, the image will not be rejected if the ear is from the same subject due to geometric changes. Unlike, Gabor and POEM, the results show high sensitivity to both illumination changes and geometrical changes which may not be easy to analyse such results on geometrical changes.

In addition, the combination of both LBP and HOG can improve the results of ear recognition, this is because: LBP and HOG features have advantages over Gabor wavelet with less computational time of feature extraction and smaller number of feature vector dimensions. Besides, HOG is great at capturing edges and corners in images. On the other hand, LBP captures the local patterns. Ultimately HOG and LBP captures different kinds of information, which make these methods complimentary to each other for geometrical changes.

V. CONCLUSION

The comparison of ear recognition methods has been presented. Compared methods are HOG, LBP, Gabor filter based, and POEM. These methods have shown sensitivity to both illumination and geometrical changes. These methods were evaluated on the database that we have created which contains 1000 images for geometrical changes and 1000 images for illumination changes. The findings from this study are that the combination of HOG and LBP can be the most suitable methods since HOG is less sensitive to illumination changes and LBP shows more sensitivity to geometrical changes. Although HOG and LBP also have weaknesses in object detection, the modifications and improvements that have been proposed by lot of researchers can overcome the weaknesses.

As for future works, we will re-evaluate the results obtained once sufficient longitudinal data for ear images of children is obtained.

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