Demographic Bias in Biometrics: A Survey on an Emerging Challenge

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Abstract—Systems incorporating biometric technologies have become ubiquitous in personal, commercial, and governmental identity management applications. Both cooperative (e.g., access control) and non-cooperative (e.g., surveillance and forensics) systems have benefited from biometrics. Such systems rely on the uniqueness of certain biological or behavioural characteristics of human beings, which enable for individuals to be reliably recognised using automated algorithms.

Recently, however, there has been a wave of public and academic concerns regarding the existence of systemic bias in automated decision systems (including biometrics). Most prominently, face recognition algorithms have often been labelled as “racist” or “biased” by the media, non-governmental organisations, and researchers alike.

The main contributions of this article are: (1) an overview of the topic of algorithmic bias in the context of biometrics, (2) a comprehensive survey of the existing literature on biometric bias estimation and mitigation, (3) a discussion of the pertinent technical and social matters, and (4) an outline of the remaining challenges and future work items, both from technological and social points of view.

Index Terms—Biometrics, bias, bias estimation, bias mitigation, demographics, fairness.

I. INTRODUCTION

Artificial intelligence systems increasingly support humans in complex decision-making tasks. Domains of interest include learning, problem solving, classifying, making predictions, and risk assessments. Such automated algorithms have in many cases advanced to perform better than humans and hence are used to support or replace human operators [1]. Those systems, referred to as “automated decision systems”, can yield various benefits, including an increased efficiency and decreased monetary costs. At the same time, a number of ethical and legal concerns have been raised in this context, specifically relating to the transparency, accountability, explainability, and fairness of such systems [2]. Automated algorithms can be utilised in diverse critical areas such as criminal justice [3], healthcare [4], creditworthiness [5], and others [6], hence often sparking controversial discussions w.r.t. the aforementioned concerns. This article focuses on algorithmic bias and fairness in biometric systems w.r.t. demographic attributes. In this context, an algorithm is considered to be biased if statistically significant differences in its operation can be observed for different demographic groups of individuals (e.g., females or dark-skinned people), thereby arbitrarily privileging and disadvantaging certain groups of individuals.

A. Motivation

The interest and investment into biometric technologies is large and rapidly growing according to various market value studies [7], [8], [9]. Biometrics are utilised widely by governmental and commercial organisations around the world for purposes such as border control, law enforcement and forensic investigations, voter registration for elections, as well as national identity management systems. Currently, the largest biometric system is operated by the Unique Identification Authority of India, whose national ID system (Aadhaar) accommodates almost the entire Indian population of 1.25 billion enrolled subjects at the time of this writing, see the online dashboard [10] for live data.

In recent years, reports of demographically unfair/biased biometric systems have emerged (see section III), fueling a debate on the use, ethics, and limitations of related technologies between various stakeholders such as the general population, consumer advocates, non-governmental and governmental organisations, academic researchers, and commercial vendors. Such discussions are intense and have even raised demands and considerations that biometric applications should be discontinued in operation, until sufficient privacy protection and demographic bias mitigation can be achieved [11]. Algorithmic bias is considered to be one of the important open challenges in biometrics by Ross et al. [11].

B. Article Contribution and Organisation

In this article, an overview of the emerging challenge of algorithmic bias and fairness in the context of biometric systems is presented. Accordingly, the biometric algorithms which might be susceptible to bias are summarised; furthermore, the existing approaches of bias estimation and bias

https://www.banfacialrecognition.com/
https://www.cnet.com/news/facial-recognition-could-be-temporarily-banned-for-law-enforcement-use/
https://www.theguardian.com/technology/2020/jan/17/eu-eyes-temporary-ban-on-facial-recognition-in-public-spaces
https://www.biometricupdate.com/202001/eu-no-longer-considering-facial-recognition-ban-in-public-spaces
mitigation are surveyed. The article additionally discusses other pertinent matters, including the potential social impact of bias in biometric systems, as well as the remaining challenges and open issues in this area.

The remainder of this article is organised as follows: relevant background information is provided in section [II] Section [III] contains a comprehensive survey of the scientific literature on bias estimation and mitigation in biometric systems. Other relevant matters are discussed in section [IV], while concluding remarks and a summary are presented in section [V].

II. BACKGROUND

The following subsections provide relevant background information w.r.t. the topic of bias in automated decision systems in general (subsection [II-A]) and the basics of biometric systems (subsection [II-B]). Furthermore, due to the sensitive nature of the topic of this article, subsection [II-C] outlines the choices made w.r.t. the nomenclature used throughout the article.

A. Bias in Automated Decision Systems

In recent years, numerous concerns have been raised regarding the accuracy and fairness of automated decision-making systems. For instance, many studies regarding the risk assessment and welfare distribution tools found a number of issues concerning systemic bias and discrimination of the systems’ predictions (e.g. against African-Americans). The impact of such systems on the lives of the affected individuals can be tremendous, e.g. increased probability of being denied a bail, parole, or welfare payments. Demographics-based bias and discrimination are especially concerning in this context, even if it occurs unintentionally. One would intuitively expect that certain decisions be impacted exclusively by hard facts and evidence, and not factors often associated with discrimination – such as sex or race, or other context-specific discriminatory factors. Nonetheless, biases in decision-making are a common occurrence; along with notions of fairness, this topic has been extensively studied from the point of view of various disciplines such as psychology, sociology, statistics, and information theory. Recently, the field of bias and fairness in automated computer algorithms and machine learning has emerged.

A good discussion of the topic of bias was provided by Danks and London, as well as Friedman and Nissenbaum, both of which explored various sources and types of bias in the context of computer systems. In many cases, bias in the automated decision systems is directly related to the human designers or operators of a system, whereas bias in automated decision algorithms is indirectly related to the human designers or operators of a system. Semi-automatic decision systems are a good example of this. In such systems, a human decision maker can be aided by an algorithm (e.g. risk-assessment). In such cases, errors in interpretation of the results of the system might occur; in other words, the human might misunderstand or misrepresent the outputs or general functioning principles of an algorithm. Furthermore, it has been shown that humans in general tend to over-rely on such automated systems, i.e. to overestimate the accuracy of their results. While human cognitive biases are an important and actively researched topic, this article focuses exclusively on bias occurring in the context of automated algorithms themselves. Human cognitive biases have been analysed, e.g. by Evans, whereas bias in human interactions with automated systems was explored, e.g. by Parasaruman and Manzey.

In the context of automated decision algorithms themselves, numerous potential bias causes exist. Most prominently, the training data could be skewed, incomplete, outdated, disproportionate or have embedded historical biases, all of which are detrimental to algorithm training and propagate the biases present in the data. Likewise, the implementation of an algorithm itself could be statistically biased or otherwise flawed in some way, for example due to moral or legal norms, poor design, or data processing steps such as parameter regularisation or smoothing. For more details on the topic of algorithmic bias in general, the reader is referred to Evans, Danks and London, Friedman and Nissenbaum. In the next sections, an introduction to biometric systems is provided, followed by a survey on bias in such systems specifically.

B. Biometric Systems

Biometric systems aim at establishing or verifying the identity or demographic attributes of individuals. In the international standard ISO/IEC 2382-37, “biometrics” is defined as: “automated recognition of individuals based on their biological and behavioural characteristics”. Humans possess, nearly universally, physiological characteristics which are highly distinctive and can therefore be used to distinguish between different individuals with a high degree of confidence. Example images of several prominent (in terms of use in deployed systems around the world) biometric characteristics are shown in figure 1.

![Examples of biometric characteristics](image)

Fig. 1: Examples of biometric characteristics (images taken from publicly available research databases).

Broadly speaking, an automated biometric system consists of: (1) a capture device (e.g. a camera), with which the biometric samples (e.g. images) are acquired; (2) a database which stores the biometric information and other personal data; (3) signal processing algorithms, which estimate the quality of the acquired sample, find the region of interest (e.g. a face), and extract the distinguishing features from it; (4) comparison and decision algorithms, which enable ascertaining of similarity of two biometric samples by comparing the extracted feature vectors and establishing whether or not the two biometric samples belong to the same source.
In the past, biometric systems typically utilised handcrafted features and algorithms (i.e., texture descriptors, see the work of Liu et al. [29]). Nowadays, the use of machine learning and deep learning has become increasingly popular and successful. Relevant related works include e.g. [30], [31], [32], which achieved breakthrough biometric performances in facial recognition. Furthermore, promising results for deep learning-based fingerprint (see e.g. [33]) and iris (see e.g. [34]) recognition have also been achieved. For a review of deep learning techniques applied within biometrics, the reader is referred to the work of Sundararajan and Woodard [35]. For a highly comprehensive introduction to biometrics, the reader is referred to Li and Jain [36] and the handbook series [37], [38], [39], [40], [41].

C. Nomenclature

In this section, the nomenclature used throughout this article is explained. The authors note that demographic words, groups, and concepts such as “gender”, “sex”, “race”, and “ethnicity” can be extremely divisive and bear a heavy historical, cultural, social, political, or legislative load. The authors do not seek to define or redefine those terms; we merely report on the current state of the research. In the literature surveyed later on in this article, following trends can be distinguished:

1) The terms “gender” and “sex” are often used in a binary and conflated manner. The readers interested in the possible consequences of this narrow approach are referred to Keyes [42].

2) Similarly, very often no real distinction between the terms “race” and “ethnicity” is made; moreover, the typical categorisation is very coarse, only allowing for a small and finite (less than ten) possible racial/ethnic categories.

3) In general, and especially in the case of facial biometric systems, the demographic factors seem to be considered on the phenotypic basis, i.e. concerning the observable traits of the subjects (e.g., colour of the skin or masculine appearance).

Due to the demographic terms carrying a large amount of complexity and potential social divisiveness, the authors consider it best not to engage in those debates in this work, and merely reproduce and discuss the technical aspects of the current research. For the sake of consistency, certain decisions regarding the used nomenclature have to be made, especially since the surveyed literature does often seem to use the aforementioned demographic terms ambiguously or interchangeably.

Recently, in the context of biometrics, ISO/IEC has made the following separation [43], while the term “gender” is defined as “the state of being male or female as it relates to social, cultural or behavioural factors”, the term “sex” is understood as “the state of being male or female as it relates to biological factors such as DNA, anatomy, and physiology”. The report also defines the term “ethnicity” as “the state of belonging to a group with a common origin, set of customs or traditions”, while the term “race” is not defined there. While the cultural and religious norms can certainly affect biometric operations, the surveyed literature mostly considers the appearance-based features and categorisation – hence, the term “race” is used instead of “ethnicity” and the term “sex” is used instead of “gender” in accordance with ISO/IEC 22116 [43]. Finally, in the context of biometrics in general and in evaluation of biometric algorithms, the standardised biometric vocabulary is used, see ISO/IEC 2382-37 [24] and ISO/IEC 19795-1 [44].

Those limitations and imprecisions of the nomenclature notwithstanding, due to the potential of real and disparate impacts [45] of automated decision systems including biometrics, it is imperative to study the bias and fairness of such algorithms w.r.t. the demographic attributes of the population, regardless of their precise definitions.

III. BIAS IN BIOMETRIC SYSTEMS

In order to facilitate discussions of algorithmic fairness in biometric systems, Howard et al. [47] introduced following two terms:

**Differential performance** concerns the differences in (genuine and/or impostor) score distributions between the demographic groups. Those effects are closely related to the so-called “biometric menagerie” [48], [49], [50]. While the menagerie describes the score distributions being statistically different for specific individual subjects, the introduced term describes the analogous effect for different demographic groups of subjects.

**Differential outcomes** relates to the decision results of the biometric system, i.e. the differences in the false-match and false-non-match rates at a specific decision threshold.

Given that these terms have been introduced relatively recently, the vast majority of surveyed literature does not (directly) use them. However, Grother et al. [51], a highly comprehensive study of the demographic effects in biometric recognition, has conducted its benchmark utilising the terms and notions above.

Before surveying the literature on bias estimation and mitigation (subsections [III-C] and [III-D] respectively), this section begins with an outline of the biometric algorithms which might be affected by bias (subsection [III-A]) and of the covariates which might affect them (subsection [III-B]).

A. Algorithms

Similarly to other automated decision systems, human biases have been shown to exist in the context of biometrics. The so-called “other-race effect” has long been known to affect human ability to recognise faces [52]. As previously stated, the cognitive biases of humans are out of scope for this article, as it focuses on the biases in the algorithms themselves. The processing pipeline of a biometric system can consist of various algorithms depending on the application scenario and the chosen biometric characteristic. Said algorithms might be subject to algorithmic bias w.r.t. certain covariates, which are described in subsection [III-B]. Below, the most important
algorithms used in the context of biometrics are described and visualised conceptually in figure [3].

One of the most prevalent use cases of biometrics is biometric recognition. Here, the distinguishing features of biometric samples are compared with each other in order to ascertain their similarity. Such systems typically seek to (1) determine if an individual is who they claim to be (i.e., one-to-one comparison), or (2) to determine the identity of an individual by searching a database (i.e., one-to-many search). Accordingly, the following two algorithms might be used in biometric recognition:

**Verification** Referring to the “process of confirming a biometric claim through biometric comparison” [24], [44].

**Identification** Referring to the “process of searching against a biometric enrolment database to find and return the biometric reference identifier(s) attributable to a single individual” [24], [44].

The biometric samples are a rich source of information beyond the mere identity of the data subject. Another use case of biometrics is the extraction of auxiliary information from a biometric sample, primarily using the following algorithms:

**Classification and estimation** Referring to the process of assigning demographic or other labels to biometric samples [53].

Prior to the recognition or auxiliary information classification tasks, the system must acquire and pre-process the biometric sample(s). Here, most prominently, following algorithms might be used:

**Segmentation and feature extraction** Referring to the process of locating the region of interest (ROI) in a biometric sample and extracting a set of biometric features from it [36].

**Quality assessment** Referring to the process of quantifying the quality of an acquired biometric sample [54], [55].

**Presentation attack detection** Referring to the “automated determination of a presentation attack”, i.e., detecting a “presentation to the biometric data capture subsystem with the goal of interfering with the operation of the biometric system” [56], [57].

### B. Covariates

Broadly speaking, three categories of covariates relevant for the effectiveness of the biometric algorithms can be distinguished:

**Demographic** Referring to e.g., the sex, age, and race of the data subject.

**Subject-specific** Referring to the behaviour of the subject (e.g., pose or expression, use of accessories such as eyewear or make-up), as well as their interaction with the capture device (e.g., distance from a camera or pressure applied to a touch-based sensor).

**Environmental** Referring to the effects of the surroundings on the data acquisition process (e.g., illumination, occlusions, resolution of the images captured by the sensor).

Figure 2 shows example images of the aforementioned covariates using the facial biometric characteristic. While there do exist studies that investigate environmental and subject-specific covariates (e.g., [93]), this article concentrates on the demographic covariates.

### C. Estimation

Table 1 summarises the existing research in the area of bias estimation in biometrics. The table is organised conceptually as follows: the studies are divided by biometric characteristic and listed chronologically. The third column lists the
algorithms (recall subsection III-A) evaluated by the studies, while the covariates (recall subsection III-B) considered in the studies are listed in the next column. Finally, the last column outlines the key finding(s) of the studies. Wherever possible, those were extracted directly from the abstract or summary sections of the respective studies.

By surveying the existing literature, following trends can be distinguished:

1) Most of the existing studies conducted the experiments using face-based biometrics. There are significantly fewer studies on other modalities (primarily fingerprint and palmprint).

2) The majority of studies concentrated on biometric recognition algorithms (primarily verification), followed by quality assessment and classification algorithms.

3) Some algorithms have been barely investigated, e.g., presentation attack detection and pedestrian detection.

4) The existing studies almost always considered the sex covariate; the race covariate is also often addressed (possibly due to the recent press coverage [117], [118]). The age covariate is the least often considered in the context of bias in the surveyed literature. The impact of ageing on biometric recognition is an active field of research, but out of scope for this article. The interested reader is referred to e.g. [62], [77], [119], [120], [121].

5) Many of the studies focused on general accuracy rather than distinguishing between false positive and false negative errors. Recent works [47], [51] introduced and used the useful concepts of “false positive differentials” and “false negative differentials” in the context of algorithmic bias in biometrics.

6) A significant number of studies (e.g. [90], [51], [47]) conducted evaluations on sequestered databases and/or commercial systems. While their results were very valuable due to the realistic/operational nature of the data, the large scale of the used databases, as well as the testing of the state-of-the-art algorithms, reproducing or analysing their results may be impossible.

A few common findings for the evaluated biometric algorithms can be discerned:

**Quality assessment** Most of the existing studies conducted the experiments using fingerprint-based biometrics. This could be partially caused by the standardisation of reliable fingerprint quality assessment metrics [122], whereas this remains an open challenge for the face characteristic [123]. The existing fingerprint quality assessment studies indicated that the extreme ranges of the age distribution (infants and elderly) can pose a challenge for current systems [63]. Additional non-obvious biases can also occur. For example, Drozdowski et al. [124] and Osorio-Roig et al. [125] found that the presence of eyewear lowers the sample quality under objective metrics in both near-infrared and visible-wavelength iris recognition systems. The demographics disproportionately afflicted with myopia (i.e. most likely to wear corrective eyewear) are those from the “developed” countries and East Asia [126].

**Classification and estimation** Scientific literature predominantly studied face as the biometric characteristic, since the facial region contains rich information from which demographic attributes can be estimated. Several of the studies showed substantial impact of sex and race on
the accuracy of demographic attribute classification. In particular, numerous commercial algorithms exhibited significantly lower accuracy w.r.t. dark-skinned female subjects (see e.g. [79], [82]). A large body of research on the classification of sex from iris and periocular images exists, but as of yet biases in those algorithms have not been studied. Additionally, it is not clear if such classifiers rely on actual anatomical properties of the iris or merely the application of mascara [127].

**Recognition** One result which appears to be mostly consistent across surveyed studies is that of worse biometric performance (both in terms of false positives and false negatives) for female subjects (see e.g. [69] and [51]). Furthermore, several studies associated race as a major factor influencing the biometric performance. However, the results were not attributed to a specific race being inherently more challenging. Rather, the country of software development (and presumably the training data) appears to play a major role; in this context, evidence of the “other-race” effect in facial recognition has been found [68], e.g. algorithms developed in Asia were more easily recognising Asian individuals and conversely al-

| Reference | Characteristic | Algorithm(s) | Covariate(s) | Key Findings |
|-----------|----------------|--------------|--------------|--------------|
| Hicklin et al. [58] | Fingerprint | Quality | Sex | Lower quality for females. |
| Modi et al. [65] | Fingerprint | Quality, verification | Age | Lower quality and biometric performance for the elderly. |
| Frick et al. [60] | Fingerprint | Quality, verification | Sex | Higher sample quality and biometric performance for males. |
| O’Connor et al. [51] | Fingerprint | Quality, verification | Sex | Higher sample quality for males, higher biometric performance for females. |
| Yoon et al. [62] | Fingerprint | Quality, verification | Sex, age, race | Negligible correlations between sample quality and subject age; sex and race have a marginal impact on comparison scores, whereas subject’s age has a non-trivial impact for genuine scores. |
| Galbally et al. [63] | Fingerprint | Quality | Age | On average, low quality for children under 4 years and elderly (70+ years), medium quality for children between 4 and 12 years. |

| Beveridge et al. [64] | Face | Verification | Sex, age, race | Better biometric performance for older subjects, males, and East Asians. |
| Lui et al. [65] | Face | Verification | Sex, age, race | Meta-analysis of previous studies. |
| Guo et al. [68] | Face | Age estimation | Sex, race | Large impact of the training data composition on the system accuracy. |
| Grother et al. [69] | Face | Verification | Sex | More false-non-matches at fixed FMR for females than for males. |
| Phillips et al. [68] | Face | Verification | Race | Varying results depending on the demographic origin of the algorithm and demographic structure of the data subjects. |
| Klato et al. [69] | Face | Verification | Sex, age, race | Lower biometric performance for females, young, and black cohorts. |
| O’Toole et al. [70] | Face | Verification | Sex, race | The concept of “yoking” in experimental evaluation to demonstrate the variability of algorithm performance estimates. |
| Givens et al. [71] | Face | Verification | Sex, age, race | Better biometric performance for Asian and older subjects. |
| Ricanek et al. [72] | Face | Verification | Age | Poor biometric performance for children. |
| Beveridge et al. [73] | Face | Verification | Sex, race | Better biometric performance for males and Asian subjects. |
| El Khiyari et al. [74] | Face | Verification | Sex, age, race | Lower biometric performance for female, 18-30 age group, and dark-skinned subjects. |
| Deb et al. [75] | Face | Verification | Sex, race | Algorithm dependent effects of the covariates. |
| Deb et al. [76] | Face | Verification, identification | Age | Child females easier to recognise than child males. |
| Best-Rowden et al. [77] | Face | Verification | Sex, age, race | Lower comparison scores for females. |
| Michalski et al. [78] | Face | Verification | Age | Large variation of biometric performance across age and ageing factors in children. Poor biometric performance for very young subjects. |
| Buolamwini et al. [79] | Face | Sex and race classification | Race | Highest accuracy for males and light-skinned individuals; worst accuracy for dark-skinned females. |
| Rho et al. [80] | Face | Emotion classification | Race | Negative emotions more likely to be assigned to dark-skinned males. |
| Abdurahim et al. [81] | Face | Verification | Sex, age, race | Lower biometric performance for females, inconsistent results w.r.t. age and race. |
| Raji et al. [82] | Face | Sex and race classification | Sex, race | Lower accuracy for dark-skinned females. |
| Nagpal et al. [83] | Face | Verification | Age, race | Training data dependent own-age and own-race effect in DNN-based systems. |
| Srinivas et al. [84] | Face | Verification, identification | Age | Lower biometric performance for children. |
| Srinivas et al. [85] | Face | Verification, identification | Sex, age | Lower biometric performance for females and children. |
| Mathukumar et al. [86] | Face | Sex classification | Race | Lower accuracy for dark females; importance of not only skin type, but also luminance in the images on the results. |
| Krishnapriya et al. [87] | Face | Quality, verification | Race | Lower rate of ICAO compliance [88] for the dark-skinned cohort, fixed decision thresholds not suitable for cross-cohort biometric performance benchmark. |
| Vera-Rodriguez et al. [89] | Face | Verification | Sex | Lower biometric performance for females. |
| Howard et al. [90] | Face | Verification | Sex, age, race | Evaluates effects of population homogeneity on biometric performance. |
| Cook et al. [91] | Face | Verification | Sex, age, race | Genuine scores tend to be worse for females than males. |
| Denton et al. [92] | Face | Classification | CelebA dataset attributes | Generative adversarial model which can reveal biases in a face attribute classifier. |
| Garcia et al. [93] | Face | Verification, presentation attack detection | Sex, race | Higher inter-subject distance for Caucasians than other groups; morphing attacks much more successful for Asian females. |
| Lu et al. [94] | Face | Verification | Sex, age, race, other | Lower biometric performance for females; better biometric performance for middle-aged subjects. |
| Wang et al. [95] | Face | Verification | Race | Higher biometric performance for Caucasians. |
| Grother et al. [96] | Face | Verification, identification | Sex, age, race | Large-scale benchmark of commercial algorithms. Algorithm dependent false positive differentials w.r.t. race. Consistently elevated false positives for female, elderly and very young subjects. Algorithm specific false negative differentials, also correlated with image quality. |
| Uhl et al. [97] | Palmprint | Verification | Age | Lower biometric performance for very young subjects. |
| Xie et al. [98] | Palmprint | Sex classification | Sex | Higher accuracy for females. |
| Brandiao et al. [99] | Unconstrained | Pedestrian detection | Sex, age | Higher miss rate for children. |
TABLE II: Summary of studies concerning bias mitigation in biometric systems.

| Reference            | Characteristic          | Algorithm(s)                     | Method(s)                                                                 |
|----------------------|-------------------------|----------------------------------|--------------------------------------------------------------------------|
| Klare et al. [69]    | Face                    | Verification, identification     | Balanced training dataset or dynamic matcher selection based on the demographic attributes. |
| Guo et al. [70]      | Race                    | Age classification               | Dynamic classifier selection based on the demographic attributes.         |
| Suo et al. [71]      | Sex                     | Sex classification               | De-identification.                                                      |
| Ohman et al. [103]   | Race                    | Sex classification               | De-identification.                                                      |
| Rya et al. [113]     | Age                     | Sex and race classification      | Twofold transfer learning, balanced training dataset.                    |
| Guo et al. [72]      | Race                    | Verification, identification     | Imbalanced learning.                                                    |
| Mirjalili et al. [104]| Race                   | Sex classification               | De-identification.                                                      |
| Acien et al. [105]   | Sex                     | Verification, identification     | Suppression of DNN features related to sex and race.                    |
| Chhabra et al. [106] | Race                    | Sex classification               | De-identification.                                                      |
| Deb et al. [73]      | Race                    | Face verification, identification| Training fine-tuning.                                                   |
| Michalski et al. [74]| Sex                     | Face verification                | Dynamic decision threshold selection.                                   |
| Das et al. [107]     | Race                    | Sex, age, and race classification| Multi-task CNN with dynamic joint loss.                                 |
| Alvi et al. [108]    | Race                    | Sex, age, and race classification| Bias removal from DNN embeddings.                                        |
| Srinivas et al. [75] | Age                     | Face verification                | Score-level fusion of algorithms.                                        |
| Krishnamurthy et al. [76] | Race          | Face verification                | Cohort-dependent decision thresholds.                                    |
| Vera-Rodriguez et al. [69] | Age            | Face verification                | Covariate-specific or covariate-balanced training.                      |
| Amini et al. [109]   | Age                     | Face detection                   | Unsupervised learning, sampling probabilities adjustment.                |
| Kortylewski et al. [110]| Race              | Face verification                | Synthetic data use in algorithm training.                                |
| Terhörst et al. [111]| Race                   | Face and age classification      | Suppression of demographic attributes.                                   |
| Srinivas et al. [77] | Race                    | Face verification                | Curating training data (noisy label removal) using automatic sex estimation and clustering. |
| Wang et al. [112]    | Race                    | Face verification                | Reinforcement learning, balanced training datasets.                      |
| Terhörst et al. [113] | Race                   | Face verification                | Individual fairness through fair score normalisation.                    |
| Bekele et al. [115]  | Unconstrained           | Soft-biometric classification    | Weighing to compensate for biases from imbalanced training dataset.      |
| Wang et al. [116]    | Unconstrained           | Classification                   | Introduces concepts of dataset and model leakage; adversarial debiasing network. |

D. Mitigation

Table II summarises the existing research in the area of bias mitigation in biometrics. Similarly to above, related work here focuses predominantly on face as biometric characteristic. In this context, mainly recognition and classification algorithms have been analysed. Generally speaking, the existing approaches can be assigned to following categories:

De-identification: Those approaches aimed to remove, change, or obfuscate certain information (e.g., demographics) either from the image (e.g., [100]) or feature (e.g., [103]) domain, often through a form of adversarial learning. The rationale is that a system trained on such data should not exhibit biases w.r.t. to the de-identified demographic covariates. De-identification methods can also be applied in biometric privacy-protection in general (see e.g., [129]).

Training: Learning-based methods have experienced a tremendous growth in accuracy and popularity in recent years. As such, the training step is of critical importance for the used systems and mitigation of demographic bias. The existing techniques mainly rely on demographically balanced training datasets (e.g., [94]) and synthetic data to enhance the training datasets (e.g., [110]). A number of balanced training datasets has been released to the research community, as shown in table III.

Dynamic selection: Deviating from preventing demographic bias, some methods attempted to employ a bias-aware approach. Examples in this category include dynamic selection of the recognition algorithms (e.g., [66]) or decision thresholds (e.g., [87]) based on demographic attributes of the individual subjects.

IV. DISCUSSION

In this section, several issues relevant to the topic of this paper are discussed. Concretely, subsection IV-A addresses the topic of algorithmic fairness in general, while subsection IV-B does so in the context of biometrics specifically. Subsection...
TABLE III: Summary of existing datasets for bias-related research in biometrics.

| Reference          | Characteristic | Size          | Details                                                                 |
|--------------------|----------------|---------------|-------------------------------------------------------------------------|
| Azizpour et al.    | Face           | ~1,000 images | Subset of FERET dataset balanced w.r.t. sex and race                    |
| Buolamwini et al.  | Face           | ~1,000 images | Images of parliamentarians balanced w.r.t. sex and race                 |
| Alvi et al.        | Face           | 14,000 images | Scraped images balanced w.r.t. race                                     |
| Alvi et al.        | Face           | 60,000 and 80,000 images | Subset of IJDB-Faces dataset balanced w.r.t. sex and race             |
| Medier et al.      | Face           | ~1 million images | Demographic and geometric annotations for selected images from YFCC-100M dataset |
| Kärkkäinen et al.  | Face           | ~100,000 images | Subset of YFCC-100M dataset balanced w.r.t. sex, race, and age        |
| Wang et al.        | Face           | ~650,000 images | Subset of MS-Celeb-1M dataset balanced w.r.t. race                     |
| Morales et al.     | Face           | ~100,000 images | Subset of MegaFace dataset balanced w.r.t. sex                         |

IV-C illustrates the importance of further research into algorithmic bias and fairness in biometrics by describing the social impact of biased systems.

A. Algorithmic Fairness in General

The challenge of fairness is common in numerous applications of algorithms, machine learning, and computer vision, i.e., it is by no means limited to biometrics. For a comprehensive survey of bias in automated algorithms in general, the reader is referred to e.g., [156], [157]. In addition to algorithmic fairness, algorithmic transparency, explainability, interpretability, and accountability (see e.g., [135], [136], [137], [138]) have also been heavily researched in the recent years both from the technical and social perspective. The current research in the area of algorithmic fairness concentrates on the following topics:

- Theoretical and formal definitions of bias and fairness (see e.g., [139], [16], [140]).
- Fairness metrics, software, and benchmarks (see e.g., [141], [142], [143]).
- Societal, ethical, and legal aspects of algorithmic decision-making and fairness therein (see e.g., [144], [11], [145], [146], [147]).
- Estimation and mitigation of bias in algorithms and datasets (see e.g., [148], [149], [150], [151], [152], [153]).

Despite decades of research, there exists no single agreed coherent definition of algorithmic fairness. In fact, dozens of formal definitions (see e.g., [139] and [140]) have been proposed to address different situations and possible criteria of fairness. Certain definitions, which are commonly used and advocated for, are even provably mutually exclusive [154]. Therefore, depending on the definition of fairness one chooses to adopt, a system can effectively always be shown to exhibit some form of bias. As such, the “correct” approach is essentially application-dependent. This in turn necessitates a keen domain knowledge and awareness of those issues from the system operators and stakeholders, as they need to select the definitions and metrics of fairness relevant to their particular use-case. Research in this area strongly suggests that the notion of fairness in machine learning is context-sensitive [155], [156]; this presumably also applies to the field of biometrics, especially for the ML-based systems. In the next subsection, the notions of fairness and bias are discussed in the context of biometrics specifically based on the literature surveyed in section III.

B. Algorithmic Fairness in Biometrics

Although the topic of bias and fairness in biometrics has emerged relatively recently, it has quickly established itself as an important and popular research area. Several high-ranking conferences featured special sessions [177] on the topic. ISO/IEC conducted large-scale evaluations [51], while ISO/IEC is currently preparing a technical report on this subject [43]. Likewise, a significant number of scientific publications has appeared on this topic (surveyed in section III). Most existing studies concentrate on face as a biometric characteristic – more research is urgently needed for other biometric characteristics, e.g., fingerprints [157]. Existing studies primarily address the following aspects:

1) Evaluations with the aim of quantitatively ascertaining the degree of demographic bias in various biometric algorithms.
2) Methods which seek to mitigate the effects of demographic bias in various biometric algorithms.

The existing bias estimation studies have uncovered a few trends w.r.t. algorithmic bias and fairness in biometric algorithms (recall subsection III-C). However, it should be noted that:

1) In many cases the biases were algorithm-specific, i.e., in the same benchmark some of the algorithms exhibited a certain bias (e.g., lower biometric performance for a certain demographic group), while others did not. In aggregate, however, the existing studies did seem to agree on certain points, as described in subsection III-C.
2) While a high relative increase in error rates for a certain demographic group may appear quite substantial, its importance in absolute terms could be negligible, especially for very accurate algorithms which hardly make any errors whatsoever [51].

Those caveats notwithstanding, the commitment of the academic researchers and commercial vendors to researching algorithmic fairness is especially important for the public perception of the biometric technologies. The field of algorithmic fairness in the context of biometrics is in its infancy and a large number of research areas are yet to be comprehensively addressed (cf. subsection IV-A):

1) Limited theoretical work has been conducted in this field specifically focusing on biometrics. Indeed, the majority of the publications surveyed in section III do not approach the notions of bias and fairness rigorously; rather, they tend to concentrate on an equivalent of some of the...
simpler statistical definitions, such as group fairness and error rate parity. Extending the existing works to consider other and more complex notions of fairness could be seen as an important future work item in the field.

2) In addition to empiric studies (especially in the case of bias mitigation, see subsection III-D), stricter theoretical approaches need to be pursued in order to provably demonstrate the bias-mitigating properties of the proposed methods.

3) Isolating the effects of the demographic factors from other confounding factors (i.e. the environmental and subject-specific covariates, such as illumination and use of accessories) is a challenging task, which is not sufficiently addressed in many of the existing studies. An example of a study which partially addressed those issues in a systematic manner is the work of Grother et al. [51].

4) Comprehensive independent benchmarks utilising various algorithmic fairness measurement methodologies and metrics are, as of yet, lacking. Only recently, in [51], one of the first independent benchmarks of biometric recognition algorithms has been conducted. Similar and more extensive benchmarks for other biometric algorithms (recall subsection III-A) are needed.

In the next subsection, the possible consequences of failing to appropriately address the issues of algorithmic fairness in biometrics are discussed.

C. Social Impact

Numerous studies described the potential of real harms as a consequence of biased algorithmic decision-making systems [144, 158] in general. Regarding biometric systems in particular, facial recognition technologies have been the main focus of such discussions (see e.g. [159]). Here, a distinction has to be made between the potential harms caused by errors and demographic biases in such systems. This heavily depends on the context and application scenario. On one hand, this could be mere inconveniences e.g. in access control systems or personal devices where additional authentication attempt(s) might be necessary due to false rejections. On the other hand, substantial personal harms and injustices could also happen due to false positives in surveillance scenarios, e.g. higher arrest rates experienced by certain demographic groups as a direct effect of biased facial recognition algorithms [160].

At the same time, it is also clear that facial recognition technology can be highly accurate, given that the images are captured with a high-resolution camera, proper lighting, and image quality controls, as well as high-quality comparison algorithms [51]. In such cases, the absolute error rates can become vanishingly small, rendering the relative imbalance of error rates across demographic groups insignificant. It should be noted, that there are no indications of the algorithmic biases in biometrics being deliberately put into the algorithms by design; rather, they are typically a result of the used training data and other factors. However, one should also be mindful, that as any technology, biometrics could be used in malicious or dystopian ways (e.g. privacy violations through mass-surveillance [161] or “crime prediction” [162]).

In a broader context, algorithmic bias and fairness is one of the topics in the larger discourse on ethical design in artificial intelligence (AI) systems [163], most prominently encompassing:

- Transparency,
- Accountability,
- Explainability, and
- Fairness.

Currently, the legal and societal scrutiny of the technologies utilising automated decision systems seems to be insufficient. However, recent legislation in the European Union [164, 165] constitutes a step in that direction. Below, several social and technological provisions, which might be considered in this context, are listed.

- Carefully selecting the data used to train the algorithms is the first and perhaps the most important step: inherent biases in training data should be avoided wherever possible. Furthermore, the size of the dataset matters – some systems have been reported to be trained on very small datasets (in the order of thousands of items), which is usually wholly insufficient to show that the data generalises well.
- Higher degree of transparency and/or independent insight into data and algorithms, as well as validation of the results could be established to foster the public trust and acceptance of the systems.
- Thresholds for acceptable accuracy (i.e. how much the systems can err) could be established legally, as well as reviewed and validated periodically. It is clear, that any predictive algorithm is unlikely to be perfect, but at the very least, from a purely pragmatic point of view, such systems should exhibit accuracy which is demonstrably at least as good as that of a human expert.
- Special training of the personnel dealing with the systems could be established to make them aware of the potential issues and to establish proper protocols for dealing with them.
- Due diligence could be legally expected from vendors of such systems, i.e. in reasonably ensuring some or all of aforementioned matters and rectifying problems as they come up. Additionally, certain accountability provisions could be incorporated to further facilitate this.

The issues of fairness (including algorithmic fairness) are complicated from the point of view of the legislation – a somewhat deep understanding of statistics, formal fairness definitions, and other concepts is essential for an informed discourse. Furthermore, the ethical and moral perceptions and decisions are not uniform across different population demographics and by geographical location. One very recent related experiment demonstrating this divergence is worth mentioning: the “Moral machine experiment” of Awad et al. [166], where a massive worldwide digital survey for an extended version of the famous “trolley problem” was conducted and its results analysed. Such results reinforce an important dilemma regarding the regulation of the automated decision systems – since many situations are morally and ethically ambiguous to humans, how should they be able to encode ethical decision-making
into laws? Once that issue is somehow surmounted, there also remains the issue of feasibility of technical solutions, as described in previous two subsections.

Currently, many laws and rules exist (international treaties, constitutions of many countries, and employment law) which aim to protect against generic discrimination on the basis of demographics [167]. However, historically, the enforcement of those has been fraught with difficulties and controversies. In this context, the algorithmic decision systems are merely one of the most recent and technologically advanced cases. The policymakers and other stakeholders will have to tackle it in the upcoming years in order to develop a legal framework similar to those already governing other areas and aspects of the society [168].

V. Summary

This article has investigated the challenge of demographic bias in biometric systems. Following an overview of the topic and challenges associated therewith, a comprehensive survey of the literature on bias estimation and mitigation in biometric algorithms has been conducted. It has been found that demographic factors can have a large influence on various biometric algorithms and that current algorithms tend to exhibit some degree of bias w.r.t. certain demographic groups. Most of the effects are algorithm-dependent, but some consistent trends do also appear.

Biased automated decision systems can be detrimental to their users, with issues ranging from simple inconveniences, through disadvantages, to lasting serious harms. This relevance notwithstanding, the topic of algorithmic fairness is still relatively new and with many unexplored areas, few legal and practical provisions in existence. Recently, a growing academic and media coverage has emerged, where the overwhelming consensus appears to be that such systems need to be properly assessed (e.g. through independent benchmarks), subjected to some degree of transparency, accountability, and explainability in addition to guaranteeing some fairness definitions. Furthermore, it appears that, in certain cases, legal provisions might need to be introduced to regulate these technologies.

Automatic decision systems (including biometrics) are experiencing a rapid technological progress, thus simultaneously holding a potential of beneficial and harmful applications alike, as well as unintentional discrimination. Zweig et al. [13] even argued that the issues (including, but not limited to bias and fairness) concerning algorithmic decision systems are directly related to the so-called “quality of democracy” measure of countries. As such, developing proper frameworks and rules for such technologies is a large challenge which the policymakers and the society as a whole must face in the upcoming future [169], [170].

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