A. Brömme, N. Damer, M. Gomez-Barrero, K. Raja, C. Rathgeb,
A. Sequeira, M. Todisco and A. Uhl (Eds.): BIOSIG 2022,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2022

Verification Failures: Assessing the Sample Quality of Fingerprints collected in an African Election Setting

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Abstract: The use of biometric technology has become an integral part of elections in Africa, the primary aim being delivery of credible elections. Fingerprint verification of eligible voters is central to this development. Deployment of fingerprint verification technology at elections has not been without its challenges for African countries. Failed verification incidents have been recorded in countries like Ghana, Kenya and Nigeria. A case is made on the need to identify the causes of these incidents before any reasonable solution can be proposed. This research investigates some of the possible causes by analysing the quality of sample fingerprints from a new dataset of an African population collected in election settings. NIST's NFIQ 2.2 was used for the fingerprint quality assessment with initial analyses reported in this work.

Keywords: Biometrics, Fingerprint Verification Failures, African Elections, Fingerprint Quality.

1 Introduction

The fingerprint is one of the oldest known biometrics and has for years been used in applications like forensics, national identification programmes, border control, electoral verification, access control etc. It is also the most popular biometric because its performance measures favourably against the required properties of biometrics i.e. universality, distinctiveness, permanence, collectability, performance, acceptability, circumvention, as well as cost [Ma09, Ng20]. The bid for more credible elections has seen the adoption of biometric technology by at least 25 Sub-Saharan African countries in recent years, as it can help reduce incidents of electoral fraud such as multiple voting and speed up electoral processes. [Pi16, CLW18] Central to adoption of this technology is fingerprint biometric verification of eligible voters. Countries that pioneered this move include Ghana, Kenya and Nigeria [CLW18, Iw18], with well-documented reports about the latter. While such large-scale deployment of fingerprint verification technology might be considered expensive, the benefits of a credible election far outweigh the cost. However, the slightest lack of trust in the technology by the electorate can result in costly consequences. It is reported that fingerprint verification has been beneficial to the electoral process of these countries but not without hitches, one of which is failure-to-verify. Kenya was reported to have recorded 4.8% failure-to-verify rate in 2017 [CLW18] while Nigeria recorded at least 10% in 2019 [Nw19]. Failure of the electronic biometric verification has

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in some situations caused its abandonment for manual verification [Iw18], a decision that could lead to distrust of the electoral process among the electorate and ultimately defeat the essence of deploying the technology. This perhaps informed the recommendation of the European Union Election Observation Mission (EU EOM) for an improvement of the recognition algorithm by the Nigerian Electoral Management Body (EMB) following the Nation's 2019 general elections [Eu19]. However, unless the causes of recorded verification failures are specifically identified, it is difficult to make any tangible technical recommendations that will help the EMBs improve the verification rates. Although the contribution of sabotage to recorded failures cannot be ignored, it is made possible by vulnerabilities due to genuine factors that could negatively influence the verification rates. Therefore, a biometric system that generally records a high verification rate is less likely to be taken advantage of. This work investigates some of the factors that could be responsible for the verification failures recorded at elections in Nigeria by assessing the fingerprint qualities from a sample population of the electorate collected in typical election settings.

2 Likely causes of recorded verification failures

A fingerprint recognition pipeline typically comprises the capturing/acquisition, enhancement, feature extraction and matching stages. The quality of a captured fingerprint image influences the output of the latter stages. A noisy (implying low quality) input image carries less of the needed information about a fingerprint and so, is more likely to result in verification failure. Generally, factors that have been identified to potentially affect the quality of fingerprint images include age, occupation, physical condition of fingertips, human-biometric-equipment-interaction (HBEI), environmental conditions, and difference in time between acquisitions [AFB15, GHB19]. The aim of this work is to investigate which of these factors contributes significantly to poor fingerprint qualities of voters during elections in Nigeria by conducting fingerprint quality assessment and analyses on a contextual dataset.

2.1 The factors in the context of an African population and election setting

Using a dataset of Portuguese origin, Galbally et al have shown that the quality of adult fingerprint degrades from about the age of forty years upwards [GHB19] . However, this finding cannot be generalised for all populations as there are other demographic-related factors that contribute to fingerprint degradations. As such, the rate of degradation, hence, quality of fingerprints for different age groups would be expected to vary across different populations. In essence, the conclusion obtained for a Portuguese population might not apply to a Nigerian population. For instance, involvement in manual work is more likely to result in fingerprints degradation [Ma09]. It is reported that farming is the main source of food and employment for about 60% of Africans [Di16], a significant number of whom work with bare hands. This statistic puts in perspective the population of Africans who engage in manual work through other jobs as well. In Nigeria for example, at least 20% of registered voters are engaged in manual work [Inec20], hence, providing some indication into the proportion of voters whose fingerprints quality might be poor. Closely associated with involvement in manual work is the presence of scars on the fingertips, another factor that could affect the quality of fingerprints.

Considering that elections in Nigeria are conducted outdoors, the impact of ambient conditions on the physical conditions of fingers cannot be overlooked. The fingertips could vary between dry and wet (sweaty), physical conditions that could adversely affect the quality of fingerprints [GEJ20]. The quality and consistency of captured fingerprint images is also dependent on the interaction of users with the fingerprint scanner, that is HBEI. Reported cases of voters who deliberately pressed their fingertips against the scanner repeatedly could negatively impact the fingerprint qualities too, an action that [Iw18] describes as a ‘bad voting habit’. These factors all potentially add up to cause variations in fingerprint qualities over a passage of time between the collection of reference and probe samples, as in the case during elections.

2.2 Why a new dataset?

These contributory factors to variations in fingerprint qualities make it essential to have a population and context-specific dataset for this work. SOCOFing [Sh18], the only notable published dataset of African origin, has only a single capture of each fingerprint from which additional ConvNet-altered samples were created. Hence, it is not ideal for a verification experiments. Because there is no available African dataset that replicates the variations described above, a new dataset of African origin was collected for this work.

3 The dataset and analyses

The dataset[4] contains fingerprint images of Nigerian volunteers, was collected in Nigeria, and in operational settings that are similar to those of the Nation’s national elections which are conducted outdoors. The age range of participants is 18 (inclusive) to 99 years. Collected metadata include age groups, gender, residence (urban or rural), occupation type, physical conditions of fingertips, history of verification difficulties at elections, environmental conditions (temperature and humidity). For all participants, the fingerprint images collected are the index fingers and thumbs of both hands. Only one of these fingers is used at the elections. There were two scan sessions for each participant and the same capturing process was followed for both sessions. 288 volunteers participated in the first session (session 1). Of these, 226 participated in the second session (session 2).

For each session, 6 impressions of each finger were collected, namely: without giving any instruction to the participants on how to place their fingertips (*uninstructed*); after the

[4] Dataset to be published after the research is concluded.

participants were given instructions on how to place their fingertips (*instructed*); "sweaty" fingertips (*sweaty*); after the fingers were wiped dry (*dry*); impressions captured from having participants press their fingers hard on the platen (*high pressure*); and impressions from having participants place their fingertips slightly on the platen (*low pressure*). For the "sweaty" impressions, participants were asked to rub each of the fingertips used on their faces one after the other before the scan, as the face is one of the sweatiest parts of the body. "Sweaty" in this context does not necessarily imply wetness because the degree of perspiration at a given time is dependent on factors like age, genetics, the environment etc, and will vary from individual to individual. The fingerprints were collected using Integrated Biometrics' Columbo 500ppi single-fingerprint scanner that is based on light emitting sensor (LES) technology [Ib17].

3.1 Fingerprint image quality assessment and analysis

The quality of each fingerprint in the dataset was determined using NIST's state-of-the-art fingerprint image quality assessment tool NFIQ 2.2[5]. The qualities were recorded against corresponding fingerprints in CSV formats, one for each scan session. Content of these CSV files would later be merged with collected metadata for analyses.

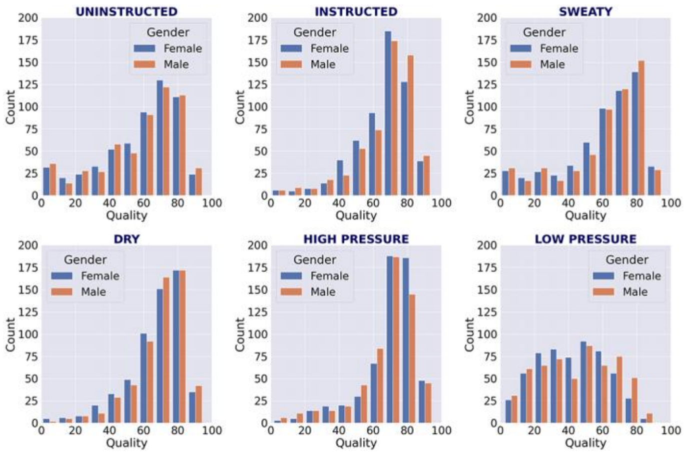

Fig. 1: Quality distribution of all impressions of all fingerprints, categorised by gender (session 1)

This section investigates how some of the factors in section 2 could contribute to the electoral verification failures in Nigeria, based on the fingerprint qualities. Fig. 1 doubles as the quality distributions of each fingerprint impression and qualities of all fingerprints, categorised by gender for session 1. An improved overall quality of the fingerprints from the uninstructed impressions to the instructed impressions is observed. There is further improvement in the relatively good quality counts for the dry and high pressure

[5] https://github.com/usnistgov/NFIQ2

impressions, whereas the low pressure impressions yield the poorest quality distribution. Notable too, is the impressive overall quality of the high pressure impressions; an observation that contradicts the suggestion by [Iw18] that the deliberate pressing of the fingertip against the scanner by some rural dwellers could be responsible for the corresponding verification failures recorded during one of the previous elections. The observed impressive quality might be attributable to the LES-based scanner that was used for the data collection for this work being less sensitive to high pressure of impression. These observations are consistent for both genders (Fig. 1) and with those from session 2 as well, notwithstanding the fewer samples in the latter.

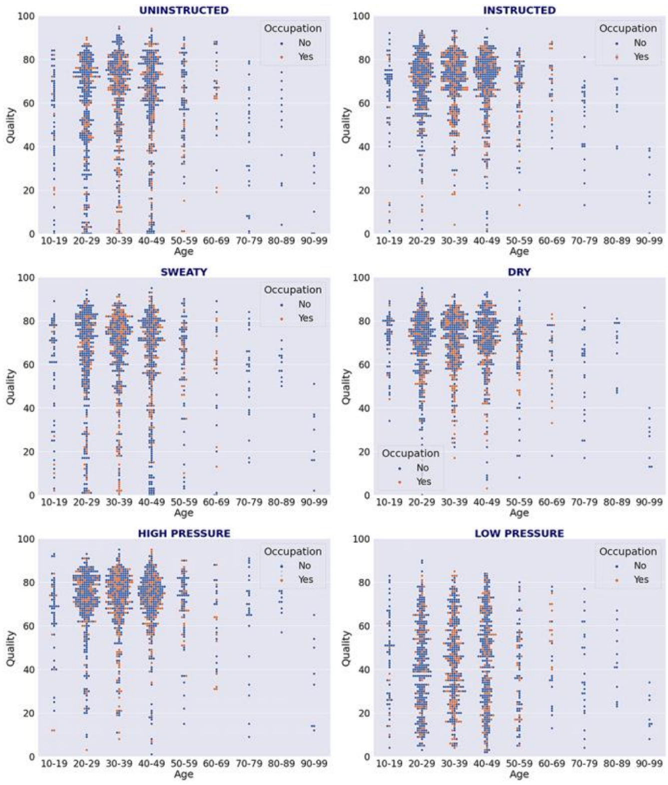

Fig. 2: Age group vs quality score of all fingerprints from a session, categorised by occupation

Fig. 2 helps assess how involvement in manual work affects fingerprint image quality while also showing the quality distributions across different age groups. ‘Yes’ on the legend signifies involvement in manual work and ‘No’ signifies otherwise. As would be expected, most participants from the age of 50 and above do not engage in occupations that require manual work. Contrary to the expectation as informed by the authors in [AFB15], there is no basis on which to conclude that involvement in manual work degrades the quality of fingerprint images. Although no one in the age range 70-99 does manual work, the quality of fingerprints in this group is relatively low. This observation could be indicative that degradation of fingerprints might be more age-dependent than occupation-dependent, where older people have lower fingerprint images qualities, albeit there are fewer samples for each age group from 50 years upwards.

A further analysis was conducted by subjecting all fingerprints from each scan session to a statistical t-test at $\alpha = 0.05$ to investigate possible statistically significant differences between the mean fingerprint qualities of those involved in manual work and those who are not. From Tab. 1, the P-values from both sessions indicate that there is no sufficient evidence that suggests that there is a statistically significant difference between both means. However, a Kruskal-Wallis H test (chosen because of the sample imbalance across the age groups) that was conducted on all fingerprints from each scan session at $\alpha = 0.05$ and degree of freedom (df) = 8 indicates statistically significant differences in medians of the fingerprint qualities between age groups (Tab. 2).

Session	t-statistic	P-value	df
1	1.7426	0.0815	3894
2	0.1546	0.8771	3054

Tab. 1: Summary of the statistical t-test for differences in fingerprint quality due to occupation

Session	P-value
1	7.9982×10^{-30}
2	3.0671×10^{-32}

Tab. 2: Summary of the Kruskal-Wallis H test on fingerprint qualities between age groups

Again, the improvement in quality of the instructed impressions compared to the uninstructed is evident across all age groups in Fig. 2. So are the qualities of the dry and high pressure impressions.

3.2 Finger-wise quality analysis

Fig. 3 provides an appreciable comparison between the quality scores of each finger, namely, left index (Quality_LI), left thumb (Quality_LT), right index (Quality_RI), right thumb (Quality_RT). Besides the uninstructed and low pressure impressions which do not have the best qualities overall, the thumbs have the best image qualities across all impressions with qualities of the index fingers being reasonably lower. A possible explanation for the good qualities of the thumbs is that they are often protected by resting on other fingers when the fists are clenched in handling objects. The practice during the Nigerian election is for voters to use either their index finger or thumbs for the verification process. Findings from the finger-wise quality assessment suggest that the use of the index fingers could be contributary to the verification failures experience owing to their relatively lower overall quality.

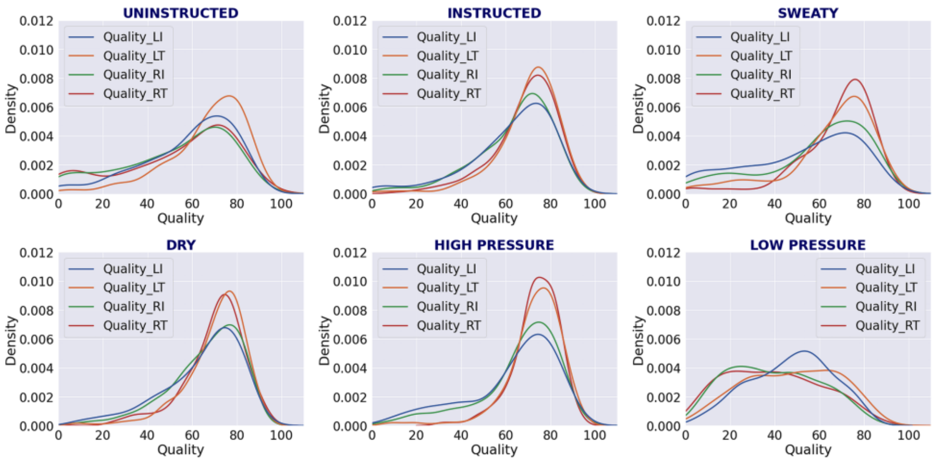

Fig. 3: Quality score density plots of the fingers from one of the scan sessions.

4 Conclusion

From the initial analyses conducted on the quality of fingerprint images from a sample of the Nigerian voting population, the following findings provide insight (that were previously unknown) into the causes of failure-to-verify cases recorded at the Nation's previous elections. Degradation of fingerprints could be more age-related than occupation-related as lower fingerprint quality is more obvious among the older voters than there is a distinction in fingerprint quality between voters who engage in manual work and those who do not. Perhaps the most obvious and easily controllable factor is HBEI related. Samples collected before instructing participants about proper placement of their fingertips have shown to have lower qualities. And deliberate pressing of the fingertip against the scanner turned out with impressive quality scores, against pressing slightly which recorded the lowest scores. Dry fingertips have also recorded fairly better qualities than sweaty ones. These observations emphasise the need for orientation of the electorate and EMB staff on proper placement of the fingertips while keeping them dry for scan. Also, they further justify recent research aimed at producing devices that require no operator such as IARPA's Nail to Nail Challenge [Ni19]. Another interesting finding is the poorer quality of the index fingers compared to the thumbs. Given that the EMB allows voters to use either their index fingers or thumbs, the overall fingerprint quality is expected to be lower than when the use of the thumbs is encouraged. Future works include comparison of qualities of scarred and unscarred fingertips, analyses of the impact of differences in weather conditions on the fingerprint images, investigating the effect of each of all factors on verification rates (including false non-match rates) and comparing these to findings from the quality analysis, and details of quantitative analyses of the observations presented in this work (as well as a post-hoc for the Kruskal-Wallis H test).

In addition, the collection of additional samples will be explored, especially for age groups with few samples, so that more reliable conclusions can be drawn from future analyses.

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