The Effect of Own-Race Bias (ORB) on Face Recognition

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Abstract. The term "own-race bias" (ORB) describes the situation in which people are more adept at identifying the faces of members of their own race than those of other races. The impact of racial disparities on face recognition accuracy and speed is investigated in this study. Empirical studies have demonstrated the involvement of variables including affect and mental abilities in ORB. While split attention tends to enhance ORB, positive emotions can decrease it. Positive emotional states may also boost cognitive flexibility, which would improve the ability to recognise faces of different races. Research looking at racial disparities in facial features also show quantifiable differences across racial groups. While some studies employ deep learning algorithms to categorise race using face traits, others use anthropometric measurements to identify these differences. Notwithstanding these discoveries, additional research employing more varied samples and longer study durations is necessary due to limitations including biassed data and a disregard for the environment.

Keywords: Own race bias, racial feature, face recognition.

1. Introduction

Face recognition is a complex cognitive process and has always been a hot topic in psychological research. Although human beings are good at recognizing the faces of their own races, they often show difficulties in accurately recognizing the faces of other races. This phenomenon is often called "ORB"—own race bias, which has great influence on law enforcement, witness testimony and social interaction. Therefore, the purpose of this study is to explore the influence of racial differences on the accuracy and speed of face recognition. Specifically, it will investigate whether individuals behave differently from other racial faces when recognizing their own racial faces. It is actually an essential topic since understanding the factors that lead to ORE is very important for solving prejudice and ensuring the fairness of applications that rely on facial recognition technology. Anyway, in order to perfect this study, a laboratory experiment will be conducted and participants with different racial identity will be invited to take a part in this study. This study aims to determine to contribute to a deeper understanding of the ORE and its implications for social psychology and related fields.

2. Factors that Related to Own-race Bias (Orb) in Face Recognition and How to Eliminate it

2.1. Emotional Factors that Related to ORB

In this part, to make this conclusion, this study use for reference. The papers by Gate and Johnson both made a research of how positive emotions influence face recognition across different races. Gates tested how positive emotions could weaken cross - rate effect, which means humans are commonly recognize faces of their own race easier than those for others' [1]. This experiment focused on a diverse sample of college students and used experimental methods, which involved emotional - inducing stimuli and several face recognition tasks. On the other hand, Johnson's paper discovered the role of positive emotions in eliminating the gap between own-race and other race faces. By using controlled lab setting with a sample of undergraduate students [2]. Anyway, both of them used experimental designs which manipulate emotional state to evaluate changes in recognition accuracy, illustrating that positive emotional feature on faces, for instance: smelling, can reduce, but not entirely eliminate, the cross-race effect. However, these two studies share shortcomings together, including a narrow demographic focus on predominantly young, college - aged participants which might not generalize across different age groups or socio- economic statuses. Additionally, the use of laboratory settings might not fully capture real- world emotional experiences and their influences on recognition. Then comes two articles that this study particularly focuses on: The studies designed by Zhou et al. and Johnson and Fredrickson. Which focus on the own -race bias (ORB) in face recognition where individuals commonly demonstrate greater accuracy in recognizing faces of their own race compared to those of other races. The research subjects in both researches were mainly people who tested for their ability to recognize faces across different races under various circumstances. First comes to the study by Zhou et al., the study was concentrated on understanding how divided attention and social clarification affects ORB [3]. All of the participants were divided into groups that some were asked to concentrate solely on the face recognition task at the same time, creating a divided attention scene. This approach aimed to simulated a real situations where attention is not always fully dedicated to a single task. The faces shown to the participants varies in race, and they were later tested on their ability to recall and tell those faces. Recognition accuracy was measured using standard recognition tests, comparing the participants' performance across different cases. The data analysis in Zhou te al's study include statistical approaches for instance Analysis of Variance to compare recognition accuracy between the focused and divided attention cases. The consequences present that ORB was shown in both cases, but it was substantially more pronounces when participants' attention is divided. This discovery suggests that cognitive resources is really a key in face recognition and when these resources are spread thin, individuals are more happen to rely on race-based calcification which will lead to stronger ORB [3]. Meanwhile, Johnson and Fredrickson (2005) discussed the influence of positive emotions on ORB. Their research assumes that positive emotions are capable to broaden cognitive and perceptual processes and might decrease ORB [4]. Participants are induced into a positive emotional stare through plenty of techniques, for example, watching happy videos or recalling a happy memory, and then facing faces of different races. This measurement included a recognition test as same as that used by Zhou et al. evaluating the accuracy of face recognition under the impact of positive emotions. To this study's data analysis, Jonson and Fredrickson used statistical approaches such as t-test to compare recognition accuracy between participants who were in a positive emotional condition and those in a neutral one. The final consequence presented a decrease in ORB when they were experiencing positive emotions which evident the idea that positive emotions can enhance cognitive flexibility and to decrease dependence on clarify thinking based on race. However, when this study comparing the two papers, we'll find that both of them showed valuable insights into ORB although from different angles. Zhou's study was mainly concentrated on cognitive factors, especially how attention distribution influence face recognition, but Johnson and Fredrickson emphasized the role of emotional states in controlling OR. Both of them have made a great contribution to understanding of ORB, suggesting that both cognitive resources and emotional states can affect how individuals tell and clarify faces of different races. Nevertheless, both studies have their own shortcomings. First of all, Zhou et al. did not mention long-term effects of divided attention on ORB. Also, they did not consider human differences like participants' cultural background or previous exposure to other races, which could influence face recognition accuracy as well. Meanwhile, Johnson and Fredrickson failed to account for how long the effects of positive emotions last or if other kinds of emotions for instance some negative or neutral may produce different results although it is in fact innovative in its study approach in which in order to examine the effect of emotions. What's more, both studies have used relatively small -size and homogenous samples, which really can't be used to make a generalization of their discoveries. In conclusion, while this study accept that both Zhou and Johnson and Fredrickson provide some complementary opinions on the mechanisms underlying ORB, further research is needed to address these gaps, especially require bigger and more diverse samples and by discovering the interactions between cognitive and emotional factors over more widely periods. This would help develop a more comprehensive understanding of the complexities included in face recognition over different races

2.2. The Effect of Some Race-related Feature in Face Recognition

In this part, this study quotes 3 references to illustrate this topic. 2 for detailed description and one for brief description.

The research on race-related variation in facial features commonly uses many diverse demographic groups, reflecting the multiformity of human populations. For example, the study by Goldstein includes a broad sample of individuals with various racial backgrounds, different age groups, gender, and socio-economic status [5]. This, again, is to capture the wide range of anthropometric data that exists within different racial groups. Such studies are often conducted with a mix of male and female participants, who usually are adults with an age range of 18 to 65 years. These participants might come from diverse socio-economic backgrounds, from low-income to high-income groups in order to ensure the properly conceived context on how both race and socio-economic status may impact the facial features.

However, the research by Khalil Khan et al. comes in with a more technology-driven approach to the analysis of racial classification through facial features. This research, even though it may deal with target population factors that are akin to these, focuses on the ways in which deep learning models can be trained on identifying and classifying race through facial features [5]. Participants in such a study would likely be representative for other racial groups as well, just as those across existing facial image databases are. The emphasis on deep learning and repeated samples indicates that a large dataset is to be used, possibly thousands of pictures involved in the process with different people's faces, so that the model can be accurate and generalized.

2.2.1 Measurement procedure/research design

Goldstein's study is characterized by an anthropometric approach, providing the measurement of facial details in racial groups. It probably makes use of tools such as calipers, photogrammetry, and 3D imaging technology for the fine measurements of different facial features, including the distance between eyes, the width of the nose, and the jawline's form.

The design is cross-sectional, in which data are collected for subjects at only one point in time, thus allowing comparison of features of the face that might differ between races. The primary purpose is to identify patterns of differences in facial structures that are connected with racial identity.

Conversely, Khalil Khan et al. utilized a deep learning framework for the identification and classification of racial features.

This study is therefore considered an experimental work in training and testing of deep learning models over large facial image datasets [6]. Preprocessed images that normalize the input to the deep learning models are then developed to detect features that would be most predictive of racial classification. The research design is, therefore, iterative, meaning the model has to be fine-tuned and tested numerous times in order to be improved in its accuracy and robustness. Data Analysis Method Probably included is multivariate analysis of variance (MANOVA), to establish the significant differences, if any, in facial measurements across different racial groups. Analytical data probably include factor analysis to establish underlying structures in facial measurements that cut across different races. Descriptive statistics would give the researcher a general idea of the central tendencies and variances in facial measurements for each racial group. Khalil Khan et al. apply popular machine learning research data analysis procedures [7]. A significant way ahead is the use of convolutional neural networks, a type of deep learning model quite appropriate for tasks in image recognition. This model will be trained with part of the data set and then tested with different instances from another data set to evaluate its performance. Metrics such as accuracy, precision, recall, and F1-score are used to access how effectively the model classifies race based on facial features. The interpretability of the learned features with regard to their contribution to racial classification can also be done using visualization techniques.

2.2.2 Conclusion and comparisons with other studies

Goldstein's study also insists that there are measurable differences in facial features among persons of different races. In fact, it inherently upholds the concept that race is partly ascribed to physical characteristics. The study further shows the overlap between groups of races. That is, although some of the variation is related to race, this relation is not absolute and must be connected to a wider context of human diversity.

This is a finding corresponding with other anthropometric studies that have unraveled similar patens, although the level of variation can be different depending on the population studied.

In contrast, the study by Khalil Khan et al. has demonstrated that high accuracy in the classification of race by facial features is possible using deep learning models [7].

That is, although anthropometric studies can be very complex and interrelated with other overlaps, deep learning models must manage to identify slight patterns of facial features that can lead to racial identity. The study also admits that bias can be created within these models if the training data do not represent the true spectrum of human diversity, a concern repeated in other research related to machine learning and facial recognition technologies.

2.2.3 Research shortcomings and defects

Even though both studies made a significant contribution, they also had their weaknesses. Though Goldstein's anthropometric measurements were very extensive, the study is likely to be biased if it entirely depended on the physical measurements of an individual. The approach does not make any adjustments for environmental factors such as nutrition and health, which are also known to affect facial features. The cross-sectional design, moreover, limits the ability to infer causality in the relationship between race and facial features. Khalil Khan et al. point to a number of issues with deep learning models. Even if such models are overall very robust, they still have bias in cases of training data that are poorly variant. More so, the models are considered black boxes, and therefore the decision-making processes are not always transparent as to exactly what this model is doing while classifying race. This can be illustrated by the fact that lack of transparency in some applications can particularly lead to problems where fairness and ethical considerations are important. All in all, these two studies greatly contribute to the question of the relationship between race and facial features but at the same time demonstrate how complex and challenging the pursued line of research is. Future studies have to try to overcome all of these limitations by working toward more diverse data sources, taking into account environmental and sociodemographic factors, and increasing transparency in deep learning models. The work of Chiroro, Tredoux, Radaelli, and Meissner is an attempt to unravel the mystery behind the phenomenon of own-race bias (ORB) in face recognition [8]. ORB is a cognitive bias where people are, on average, more accurate when recognizing faces from their racial category than those whose race is different from them. The bias emerges from the within-race variability between continents. The subjects for the experiment were drawn from diverse racial backgrounds and were required to recognize faces in their own race and in other races. The researchers gathered that ORB is a robust effect that subjects demonstrated better face recognition capabilities when the faces were of their own race. This finding concurred with several earlier studies. However, this study also noticed that within-race variability is an important factor and, therefore, the consistency of recognition accuracy might vary according to within-race feature diversities. More importantly, compared with other studies, this piece of research pointed out one significant aspect of within-race variations often neglected in ORB research.

But, however well it may be designed, drawbacks can be pinpointed in terms of possible cultural biases in recognition accuracy or sample size insufficiencies to perfectly reflect the global population. Such caveats then beg more diverse and larger sample research to cater to the fine nuances of ORB. In other words, the study confirmed the presence of ORB and signifies that nuanced research is required regarding within-race variability and fuller demographic representation in the future.

3. Conclusion

All in all, in this study, this study aimed to figure out some factor that deep related to own race bias in face recognition in order to make larger proportion of people have a deep understanding of ORB and eliminate it as possible as they could in future. Throughout the entire study this study conclude that most people are good at recognizing the emotion of their own-race individuals rather than other-race individuals. However, when people show positive emotion on their faces, individuals are easier to recognize their emotion no matter the race. In the other part of the study, this study looked for some racial feature appeared in individuals faces that may related to ORB and this study finally concluded that there are measurable differences in facial features among persons of different races. In fact, it inherently upholds the concept that race is partly ascribed to physical characteristics. The study further shows the overlap between groups of races. That is, although some of the variation is related to race, this relation is not absolute and must be connected to a wider context of human diversity. This this the end of this study.

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