

STUDY ON USEFULNESS OF STUDYING THE GEOGRAPHICAL VARIATION IN HUMAN FACIAL FEATURES



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ABSTRACT

Variation may be found in many of the visible characteristics of humans, such as the form of the brow region and the nose, the color of the skin and the eyes, the diverse qualities of body hair, and the size and proportions of the body. Since Darwin's time, there has been substantial discussion over the extent to which such diversity may be explained by genetic drift (neutral

processes), local adaptation, or sexual selection. This discussion began with Darwin (1871). One strategy for determining the relative influence of neutral versus selective processes on the differentiation of human traits is to compare the relative amounts of within-population and between-population variance.

KEYWORDS: Usefulness, Geographical, Human Facial, Genetic Drift, Local Adaptation,

INTRODUCTION

Variation may be found in many of the visible characteristics of humans, such as the form of the brow region and the nose, the color of the skin and the eyes, the diverse qualities of body hair, and the size and proportions of the body. Since Darwin's time, there has been substantial

discussion over the extent to which such diversity may be explained by genetic drift (neutral processes), local adaptation, or sexual selection. This discussion began with Darwin (1871). One strategy for determining the relative influence of neutral versus selective processes on the differentiation of human traits is to compare the relative amounts of within-population and between-population variance. This comparison can be done by looking at the amount of variation that exists within a population as opposed to the amount of variation that exists between populations. It is well known that the vast bulk of the genetic variation in humans (about 90%) is found within continental areas, whilst the variances across regions only account for a small percentage (approximately 10%) of the variation (Weir et al., 2005, Barreiro et al., 2008). The level of differentiation that may be predicted as a result of neutral evolution is widely agreed upon to correspond to such an allocation of diversity (Relethford, 2002). In genetic data, differentiation is primarily quantified using Wright's fixation index (F_{st}) (Wright, 1950). At the same time, an analogous statistic has also been created for phenotypic variation contributed to by genetic variables, and it is typically referred to as Q_{st} (Spitze, 1993). As a consequence of this, the direct comparison of F_{st} and Q_{st} serves as an efficient neutrality test for phenotypic features. In this context, significant deviations of Q_{st} from values of neutral F_{st} are suggestive of non-neutral evolution (Miller et al., 2008).

Studies of phenotypic variety and apportionment in humans have, for the most part, concentrated on characteristics that may be quantified on skeletal remains (in particular, skulls). Relethford (1994) was the first person to report that the variation among continental regions accounted for less than ten percent of the overall craniometric variation (Relethford, 1994). This finding was in good agreement with the apportionment that was based on neutral genetic loci. Relethford's study was based on 57 inter-landmark distances. Later research that utilised various sets of measurements different methods for partitioning variation 3D landmark data (Harvati and Weaver, 2006, von Cramon-Taubadel, 2009b), or different samples (Harvati and Weaver, 2006, Hubbe et al., 2009), have repeatedly come (Roseman and Weaver, 2007, von Cramon-Taubadel and Weaver, 2009, Relethford, 2010). The fact that there is a strong relationship between phenotypic distance and geographic distance is also compatible with the hypothesis that human skull variation has been influenced by neutral evolutionary processes. In addition, similar to how genetic variety can be used to infer population structure and history, human craniometric variance may be studied.

Despite this, there is a striking contrast between the relatively low degrees of differentiation of craniometric traits and the situation for skin pigmentation, which displays the largest variety

(about 80%) among groups (Relethford, 2002). It also runs counter to the commonsense belief that there is significant demographic variety in face traits across the globe. In point of fact, adaptive theories have been presented for a variety of craniofacial traits and characteristics. For instance, the form of the nose has been postulated to play a significant part in the process of climate adaptation for a very long time. Numerous studies have shown that there is a highly significant association between the nasal index (the ratio of nose breadth to height), and both the temperature and the humidity. Recent studies have also shown larger among-population differentiation values (maximum Q_{st} 0.4) than predicted under neutrality for numerous nasal measures. These results differ from what would be expected when the neutrality assumption is made (Roseman, 2004, Roseman and Weaver, 2004, Hubbe et al., 2009). Despite this, these studies have only focused on the skeletal components of the nose, which means that the external nose's soft tissues have received very little attention.

Even though the underlying skull may have been subjected to greater selection pressures than the soft-tissue facial form, there has not been a systematic study of the variation in soft-tissue facial form as of yet. This is despite the fact that the soft-tissue facial form may have been directly exposed to the environment, which may have caused it to experience greater selection pressures than the skull bones. Instead of the skull bones, selection may be responsible for shaping the distribution of the skin, cartilage, or adipose tissue. As a result, we utilised a novel methodology to investigate the variations in the soft-tissue face shape. In a nutshell, high-resolution 3D face scans were obtained from individuals belonging to four different Eurasian populations: Han Chinese from East China (HAN), Tibetans (TIB), Uygurs (UYG) (an admixed race of European and Chinese heritage), and Europeans (EUR). An innovative method for 3D facial surface alignment was used to automatically annotate 15 facial landmarks, and then a dense point-to-point correspondence was established for around 30,000 3D point markers. The resolution of the method was one point per 1 mm 1 mm surface. After that, the high-density data were brought into the same Cartesian coordinate system by utilizing generalized partial Procrustes analysis, also known as pGPA (Dryden and Mardia, 1998). Both the entire face and individual facial features were subjected to population structure and variance apportionment analyses. These analyses were carried out on both the complete face and the particular facial characteristics. We discover that variance in the soft tissue shape of the human face has been impacted not just by population history but also by selection over the course of human evolution.

RESEARCH METHODOLOGY

What do people in the southern region of Kenya look like? What does the typical resident of Tokyo look like, and how does their appearance compare to that of a person living in Jakarta or Los Angeles? Such problems are at the centre of anthropological investigations of human diversity where the conventional method places a strong emphasis on direct observation, which calls for a significant amount of laborious physical work. This places a significant restriction on the kinds of queries that may be answered. A computational model of such variances might significantly increase our understanding of modern human diversity and enable applications in a broad variety of fields, including anthropology, sociology, fashion, information security, and computer graphics, amongst others. The conjunction of these two occurrences opens the door to this particular line of inquiry. To begin, a rising number of photographs that include geotags are being published to social networking sites on a daily basis. Around 500 geotagged photographs are submitted to a major social networking site per minute, which equates to 260 million geotagged photos being uploaded every year. Second, the most recent technological advances

Computer vision algorithms have attained a level of accuracy and resilience that enables comprehensive scene information (such as people, objects, and background) to be automatically retrieved from photos. This is made possible by the advancements made in the field of computer vision.

The geographic structure of face appearance is what we hope to investigate and evaluate with this effort, and we will do so utilizing imagery that is available to the public (Figure 3.1). In order to assist in this endeavor, we built a dataset by collecting photos that were geotagged and then extracted frontal face patches that were aligned. This led to the creation of a dataset called GeoFaces, which has about 0.8 million geotagged faces. To the best of our knowledge, this is the largest dataset of its sort that is available to the public.

We apply a number of statistical models in order to investigate the location dependency of human face appearance, and we do so by utilizing the GeoFaces dataset. This research draws attention to the significant underlying patterns that have been concealed in the data. The main contributions of this work, in addition to the dataset, are as follows: (1) visualizations that highlight the geo-dependence of visual appearance. These visualizations were constructed using techniques from machine learning. (2) quantitative results that further illuminate the dependence. (3) an evaluation of several methods for estimating the location of a face at the continental, sub-continental, and country scales.

3.2 GEOFACES

We collected geotagged pictures from Flickr that included face-related metadata in order to construct GeoFaces, a big dataset consisting of geographically distributed face patches (e.g., face, portrait, men, family, friends).

A commercial face detector was utilized for each image in order to locate and identify faces and fiducial points. The detector was calibrated to discover frontal faces, or faces that were approximately frontal. In all, 3.8 million face patches were recovered from the 3.14 million pictures used. The detector reported the estimated pose direction and detection confidence for each face patch, in addition to the positions and detection confidences of specified fiducial control points (e.g., eyes, nose, mouth). A similarity transform was utilized in order to accomplish the automated alignment of each face patch to a shared reference frame. The eye centres served as the control points.



Fig. 1 Human Facial Appearance Differs for Many Reasons, Including Ethnicity, Gender, And Hair Style. In This Work, We Explore the Relationship Between Facial Appearance and Geographic Location

DATA ANALYSIS

In different parts of the world, people's faces might look very different from one another. This diversity is due to a number of factors, including the existence of facial hair, a person's attire, and their expression, in addition to the fact that ethnicity is significantly influenced by geographical location. The association between a person's geolocation and the look of their face gives significant clues that may be used to make educated guesses about a person's origin. The investigation of this connection is a developing line of inquiry that might have many different implications for various fields of study. For instance, a model that characterizes this relationship could be used to help in applications for security and surveillance that attempt to determine the identity of a suspect, detect individuals who are out of place, or in applications

DISCUSSION

The findings presented shed light on the fact that ethnicity is a crucial factor in our system's ability to make accurate forecasts. This gives rise to a reasonable follow-up question, which is, "Does the suggested system accomplish nothing more than identify ethnic groups?" In order to look into this further, we create montages of the people who rated the highest as having their photographs taken in a certain area bin (city of country). To be more specific, we place all of the faces that come from a given pair of locations into separate bins and then compute each face's score as the difference in the probability of coming from those two places. In Figure 4.1 we display the 20 faces from each city that scored the highest and had the greatest total score. By comparing neighboring cities with comparable major ethnic groups, we are able to see that there appear to be remarkable disparities in the look of individuals in these cities that are not caused by variances in their ethnic background. We also trained some one-vs-all (OVA) classifiers for a few nations that were picked from GeoFacesX as part of an extra experiment that was comparable to one that was detailed in the chapter before this one. We were able to show that the environment in which a photograph was taken has a significant impact on the way people's faces seem. This is the first effort that we are aware of that makes use of a deep convolutional neural network for the purpose of directly predicting the geo-localization of a picture. When we evaluated the performance of the suggested approach with that of two baseline techniques, we discovered that the proposed method was much superior to both. In addition, we examined the mistakes that were produced by our algorithm and discovered some intriguing trends. This demonstrates that there is a complex structure underlying the association between face appearance and geographic location, which merits more research. In this study, we only take into account a single face; nevertheless, it is expected that taking into account numerous faces inside a single image can improve the accuracy of localization.

CONCLUSION

In this dissertation, we analyze the geo-dependence of human facial appearance by using massive datasets of face patches and related geo-information that we obtained on the internet. These datasets were used to investigate human facial appearance. We use statistical methods to investigate this geo-dependence and find that there is a rich structure in this relationship that is not completely explained by differences in the distribution of ethnic or racial groups. This is something that we found out after discovering that there is a connection between the two. In our investigation, we make use of established methods for face identification and estimation,

as well as posture and appearance normalization and attribute estimation. The findings of our research underline the importance of continuously improving these fundamental algorithms. Because of these advances, the amount and quality of face image patches that we are able to employ will both grow, which will ultimately result in an increase in the accuracy of our higher-level analysis. In addition to this, we also provide an innovative method for the geo-localization of images by making use of human faces as indicators. In order to overcome this issue, we employ methods and technologies from the fields of statistics and machine learning that are both time-tested and cutting-edge. In addition, we offer a comprehensive analysis of the reliance of human face appearance on geo-location, which enables further comprehension of the connection between human facial appearance and geo-locations.

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