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Skin and Bones:
Computerised Craniofacial Reconstruction

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1 Introduction

Craniofacial reconstruction (CFR) is the process of creating a representative facial surface from available remains. CFR is a growing field in Anatomy. The traditional method involves time consuming manual reconstruction and requires considerable skill. A need has arisen for computerised methods which are less subjective and much faster to create. The intention of this project is to investigate computerised techniques and make a contribution by developing a computerised method for CFR. This method will include extra information such as age, Body Mass Index and ancestry to improve it's accuracy.

This project is focused specifically on the part of the process that estimates skin landmarks from skull landmarks. Since there is no known formal relationship between points on the skin to points on the skull, the problem can be treated as a prediction problem. The most logical way to solve the prediction problem is using statistical regression.

2 Background

This section will cover the background on the application of CFR and previous methods. The core of the CFR problem is based on a prediction model. This section will also give a background of prediction problems and the regression techniques employed to solve them.

2.1 Craniofacial Reconstruction

Traditional methods of CFR are performed manually by a forensic anthropologist. The first reconstruction was performed by the Russian anthropologist Gerasimov [1] in the late 1960s. His technique involves building layers of facial tissue on top of a skull-cast and putting a layer of skin over the top. This method, known as the morphoscopic method, is the most anatomically correct but prone to subjectivity. During this time researchers in the United States were developing a method now called the morphometric method [2]. This method differs from Gerasimov's in that it looked at average tissue depths at points on the skull to create the reconstruction, and does not involve modeling complex facial tissue. Most computerised methods are based on this paradigm. Parts of each method were combined in the late 1990s and adapted to make a combined method [3]. The combined method takes advantages of both methods like the anatomical correctness of the morphoscopic method and the non-subjective morphometric method. The shortcomings of the manual method are illustrated in [4]. The authors investigated reconstructions of the Green River Serial Killer's victims. The reconstructions were highly variable among practitioners, highlighting the subjectivity of the process. The reconstructions had varying resemblance to real life photos of the victims, proving their inconsistency and inaccuracy.

Most work done on computerised CFR has been computer assisted and still requires the skills of a human practitioner. The current techniques often do not take into account extra information such as age, Body Mass Index (BMI) and ancestry. Berar et. al. use regression to create a computer assisted method for CFR [5]. They present the problem as a prediction problem and use a Latent Root Regression model. The model performs better than the same process using Principle

Component Analysis and comparably to other methods which were not discussed. Claes proposes a Bayesian model for estimation in [6]. This uses a Gaussian model of facial features to build an accurate facial model from devised parameters, by finding the most probable face. Lee performs an accuracy assessment of computer assisted CFR in [7]. The constructions were performed on a computer in the FreeForm software by a human practitioner. The resulting skin surfaces were measured by distance from the actual surface and they found that more than half the predicted models were under 2.5mm of error. Kahler presents an ambitious computer assisted method which mimics the morphoscopic method described above [8]. Soft tissue layers are modeled onto a 3D representation of the skull with the assistance of a human practitioner. Included in these layers are facial muscles which allow the reconstructions to be animated and have varying facial expressions. The authors of this study do not test the accuracy of the method. None of the methods researched used extra information about the subject to improve their accuracy.

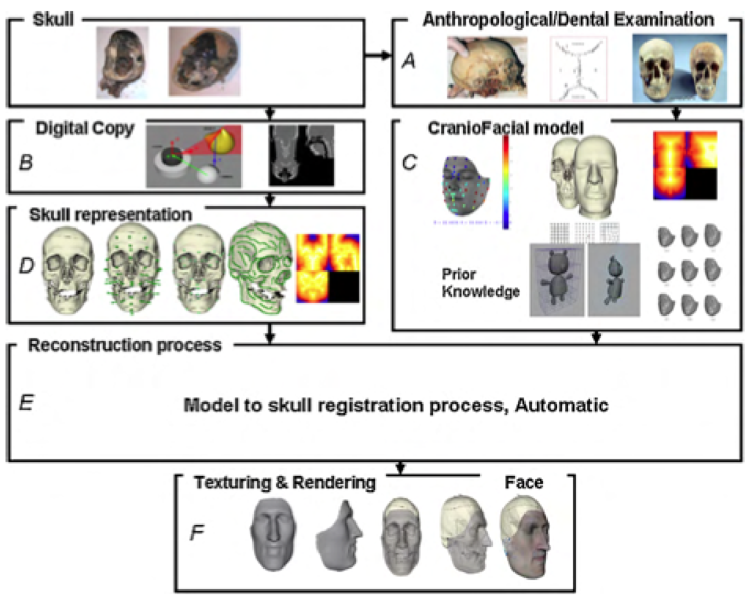

Figure 1: Craniofacial Reconstruction framework presented by [9].

A conceptual framework for computerised CFR presented by [9] is shown in figure 1. This model splits the process up into steps. The first step (a) is to perform an examination of the skull to obtain important properties such as age, gender and ancestry. Next (b) a virtual copy of the skull is created using a CT scan. The most important step in any CFR method is the Craniofacial Model(c) which represents pre-existing knowledge about the mapping of bone to skin. In (e) this model is compared with a digital representation of the skull (d) to see how the reconstruction should be made. Finally the reconstruction model can be rendered and textured (f).

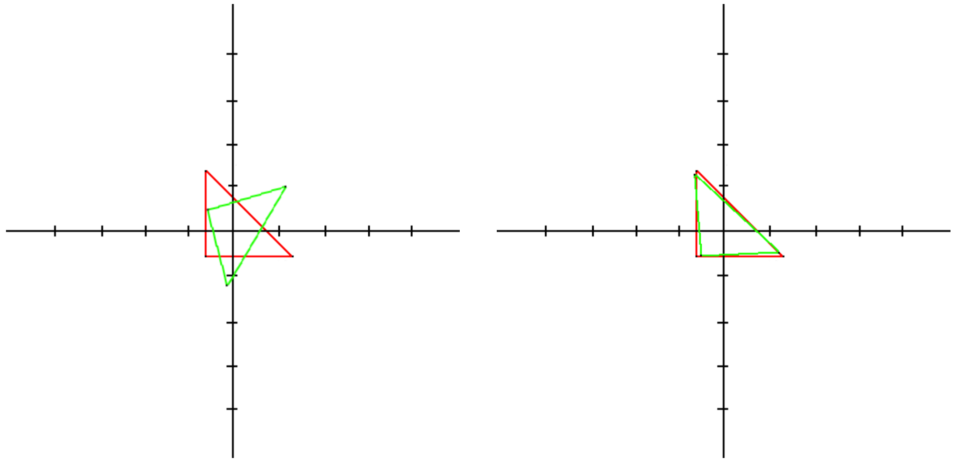

Figure 2: Ordinary Procrustes Analysis: The first picture shows the two shapes originally, the second is after the green shape has been matched to the red shape

2.2 Prediction

Prediction problems are a set of problems which require the inference of a value based on some other value(s). In the case of CFR (particularly morphometric methods) the value known is the position of points on the skull and the value required is the position of the skin which corresponds to those landmarks. Most previous computerised methods use simple average tissue depths to estimate this, but this is a poor estimation. The aim of this project is to estimate the positions based, not just on averages, but real data.

Statistical regression techniques are useful in situations where training data is available. They analyze the variables in the training data and produce estimated relationships between them. These relationships can be used to generalise using unknown data. In CFR a relationship can be estimated between bone landmarks and skin landmarks, complex regression methods can handle these relationships being complicated with dependencies on many variables.

Regression can not be performed on the raw data because it is not aligned, the accuracy will be much higher if the data is normalized first. Ordinary Procrustes Analysis (OPA) is a statistical shape analysis method. It is used to superimpose two shapes on top of each other. The result is a transformation which makes the two shapes as similar as possible. OPA fixes one of the shapes (the reference shape) and finds the optimal transformation for the other which results in it being as close as possible to the reference shape. Figure 2 is a visual example of how OPA works. Generalised Procrustes Analysis (GPA) extends this process to an arbitrary set of shapes [10]. GPA repeats OPA between one shape and the rest of the shapes until they are reasonably aligned. Now regression can be performed.

General Regression Neural Networks (GRNN) were developed by Specht [11] in the early 1990s. They use the neural network model of computing with a large number of nodes doing relatively simple calculations, meaning they can be run in parallel very easily. Equation 1 is a statistically proven method for estimating from a set of pre-known data.

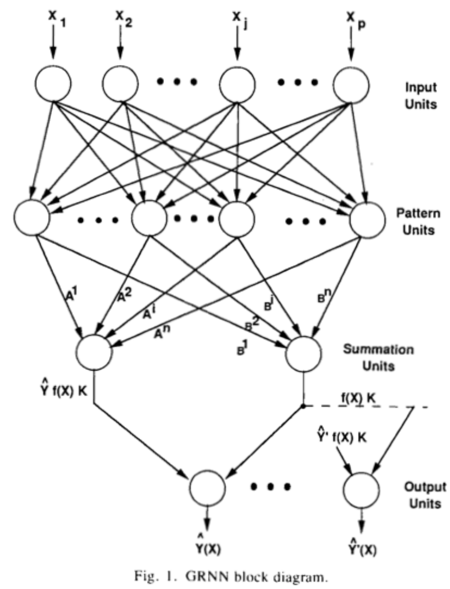

Figure 3: The architecture of the General Regression Neural Network in [11] the input units separate the input vector into its parts, the pattern units perform the correlation calculation, the summation units perform the weighted sums and the output unit(s) calculate the final quotient.

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y^i exp(-\frac{C_i}{\sigma})}{\sum_{i=1}^{n} exp(-\frac{C_i}{\sigma})} \tag{1}$$

The product of the exponential function of the correlation of X to each training sample (C_i) and that training samples expected output Y^i is summed across all the training data. Then this is divided by the sum of the exponential function of the correlation. σ is a smoothing parameter, the larger it is the smoother the resulting regressed surface will be. When σ is small the surface can take non-Gaussian shapes but outliers can have a greater effect [11]. Figure 3 shows the network architecture and how it performs the evaluation.

Support Vector Machines (SVM) are non-linear classifiers taking a set of input and predicting which of two classes forms the output [12]. Support Vector Regression (SVR) is an adaptation of SVM to estimate an unknown function $G(\mathbf{b})$ where $\mathbf{b}$ is a vector in $\mathbb{R}^n$ [13]. While SVMs and by extension SVR are linear, they can be extended to non-linear relationships through the use of kernels [12]. Kernels map the sets of observations from a general set S into an inner product space V in which they can gain meaningful linear structure. Figure 4 demonstrates linear and non-linear classification using SVMs.

The key advantage of SVR is the ability to be effective in high dimensional spaces. The model will be created from a number of landmarks giving the input space a high dimensionality. SVR is

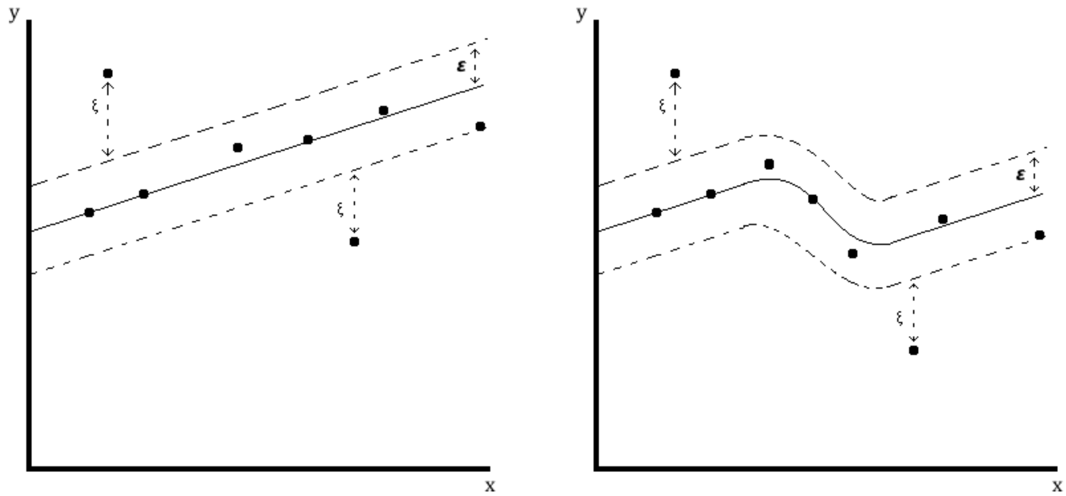

Figure 4: Support Vector Machines: SVMs can support both linear and non-linear classification using kernels. Note that any samples inside the epsilon-band are considered to have an error of zero. Classification can be extended to regression [12]

also less computationally expensive when predicting, because the decision function uses a subset containing only relevant training samples. A potential disadvantage of SVR is that if the number of features in the data is much greater than the number of samples, performance can be affected [12]. This is because SVR works by identifying features in the data.

Partial Least Squares Regression (PLSR) is a regression method for relating two data matrices. PLSR relates independent **X** and dependent **Y** by modeling the structure of **X** and **Y** using matrix ranking and scores [14]. PLSR predicts **Y** by decomposing the independent block **X** and building up **Y**.

The most desirable feature of PLSR is robustness in the face of noise and incomplete data. It will still give a good prediction even if there is not very much data to train on. A disadvantage of PLSR is the difficulty to interpret the model it creates, since this is essentially a matrix of rankings and loadings. For this reason PLSR has been suggested for use more as a predictive technique than a interpretive one [15].

These methods can all be used in CFR. No papers have currently performed a comparison of different techniques so it is not certain what their advantages and disadvantages may be when applied. Finding these advantages and disadvantages is one of the goals of the project.

3 Method

The method developed is based on Figure 1. The steps (b) and (d) have previously been performed by an Anatomy PHD student, Louisa Baillie. She gained the data from Cone Beam Computed

Topography (CBCT) images and marked the positions of 27 landmarks on the skin surface and bone surface for 60 subjects. A map of the provided landmarks is shown in the appendix. These scans came with information about the subjects such as age, BMI and approximate ancestry. This is the information required by step (a).

The model used in (c) of Figure 1 is the major focus of this project. The model can be treated as a prediction problem. Predict the estimated locations of the skin landmarks by the known skull landmarks. The method is to use the pre-existing knowledge to build up a prediction model. The pre-existing knowledge needs to be gathered and processed first in order to create an accurate model.

3.1 Data Acquisition/Normalisation

I am using R to process the data and create the model. The first step is to read in the data from a Comma Separated Value (CSV) file. Some subjects do not have locations for every landmark. Currently I strip these out and only use subjects with complete data. Later on the model can be adapted to add these subjects and for the time being they can be used as validation data. The file contains the data for every subject organised by subject number.

Before the data can be processed it must be put into a standard format. The data is converted into two separate 3-dimensional arrays (one for bone landmarks and one for skin landmarks). Each 3-dimensional array is organised by subject, then by landmark, then by co-ordinate. `array[x][y][z]` is the value of the zth co-ordinate of the yth landmark of the xth subject.

The data is not aligned due to the differing orientations of skulls in the CBCT scanner. The first step is to align the skull data using GPA. The R 'shapes' package provides an implementation of GPA which can align a set of data. The array of raw data can be passed into the GPA function for alignment. The GPA function has a tolerance which can be set to higher or lower depending on how aligned the shapes should be, I used the default of 1×10^{-5}. The results of the alignments are a clear improvement over the unstructured data. The aligned data shows clear groupings around each possible landmark. These results are shown in visual form in the appendix.

The skin data must be aligned too, GPA can not be run separately on this data because it would transform it independently and destroy the relationship between the skull and skin landmarks. The skin data must have the same transformation applied to preserve the relationship. Using OPA I can find out the transformation each subject's bone landmarks underwent. Then I apply this transformation to that subjects skin landmarks. The result is that the skin landmarks are aligned and the relationship preserved. The aligned skin data is also shown in the appendix.

3.2 Model Creation/Validation

The relationship of bone landmarks to skin landmarks is unknown and there are different forms the model could take. The simplest form (one-to-one) is to have the model regress from each bone landmark to a corresponding skin landmark individually. It is likely that the position of the skull landmark depends on more than just one bone landmark, so this will not provide a very accurate estimation. A form which addresses the problem of not enough information is to regress the entire set of skin landmarks at once from the entire set of bone landmarks (all-to-all). The relationship between bone landmark and skin landmark is likely to vary among landmarks. A problem with this form is that it will not allow for that variation. To fix this the form can be a separate model for each skin landmark that is given all the bone landmarks (all-to-one). This will allow for variation among skin landmarks. The danger with regressing from all the landmarks is that there is the potential to include irrelevant information, it is unlikely that the position of a skin landmark near the chin is dependent on a bone landmark above the eyes. This problem can be fixed by only regressing from a group of relevant bone landmarks to a particular skin landmark (group-to-one), for example the chin skin landmark is only dependent on those bone landmarks near its corresponding bone landmark. The problem with this technique is the difficulty of deciding how to group the landmarks. The first model created will be an all to one model because this is the simplest form which has a good chance of success.

The prediction model (c) will be based on the regression techniques investigated. Each of these techniques has an implementation available for use in R. The regression functions require a set of training data as input as well as a form for the regression. They create a model which can then be used to guess skin landmarks from new bone landmarks. How the prediction is calculated is based on the type of regression used. The model created can be enhanced using additional parameters such as age, BMI and ancestry.

To validate the model I will test the accuracy of its predictions. This can be done by using a validation set of data. The validation data will be a subset of the gathered data which is not included in the training data. As mentioned earlier incomplete subjects could be used for this purpose. These subjects would only be useful depending on the form of regression, for example all to one regression would require a full set of data, so complete subjects would need to be in the validation set. The predicted results will be validated by how similar they are to the real data.

4 Future Plan

At the beginning of this project I devised objectives, which were specific goals to achieve to help work towards the aim of the project. The first of these was to review current literature on machine prediction and CFR. I completed this review but have discovered another topic I need to investigate, this is how to estimate a full facial surface from a sparse sampling of points. The model will predict 27 landmarks and I will need to estimate a full surface if I want to draw an entire face.

Another objective was to research and implement GPA for normalising the data. Due to the research I have a good understanding of how GPA works. Instead of implementing GPA I adapted a library version to save time. After visualising the data both before and after alignment, as is shown in the appendix, the benefit GPA will have is very clear.

The first objective I have not mainly completed is to choose a selection of methods to test out and implement them. I have chosen a selection of regression techniques which are described in the background section. Instead of implementing these I will find pre-written versions to save time. I would also like to do some more reading in order to increase my understanding of the methods and their ideal uses.

Another objective was to investigate and test the chosen methods and select the best one based on accuracy. This will be achieved using the validation set described earlier. This objective has not been completed yet but it will not require much extra work after the methods themselves are running.

The final objective was to create a program to build faces from given skin landmarks. This is the objective which will be affected most by time constraints. If I run out of time it can be altered to reconstruct the face but not draw it, or draw a very primitive version.

5 Conclusion

Computerised craniofacial reconstruction is the process of constructing a likeness of an individual before they died. CFR is of great importance in forensic anthropology and letting us know more about important historical figures. Since most typical techniques require the skills of a human practitioner they can be time consuming and prone to subjectivity. Computerised methods fix this, however, research into the field is incomplete. Some papers suggest computerised methods to perform CFR but do not validate the results. Not many researchers have investigated the effects of auxiliary parameters such as age, BMI and ancestry.

This project aims to develop a method that can be used for computerised CFR. The focus within this method is to create a craniofacial model [9]. The model will represent the pre-existing information about the mapping of bone to skin. This information will be found by analyzing data using a selection of regression techniques. The data was obtained by Anatomy PHD student Louisa Baillie.

The project is incomplete and there remains work to be done. Now that the data has been processed most of what remains is to create the model using the collected data. Techniques for building a facial surface from a sparse sampling of points will need to be reviewed. These techniques can then be adapted to draw the reconstructed face.

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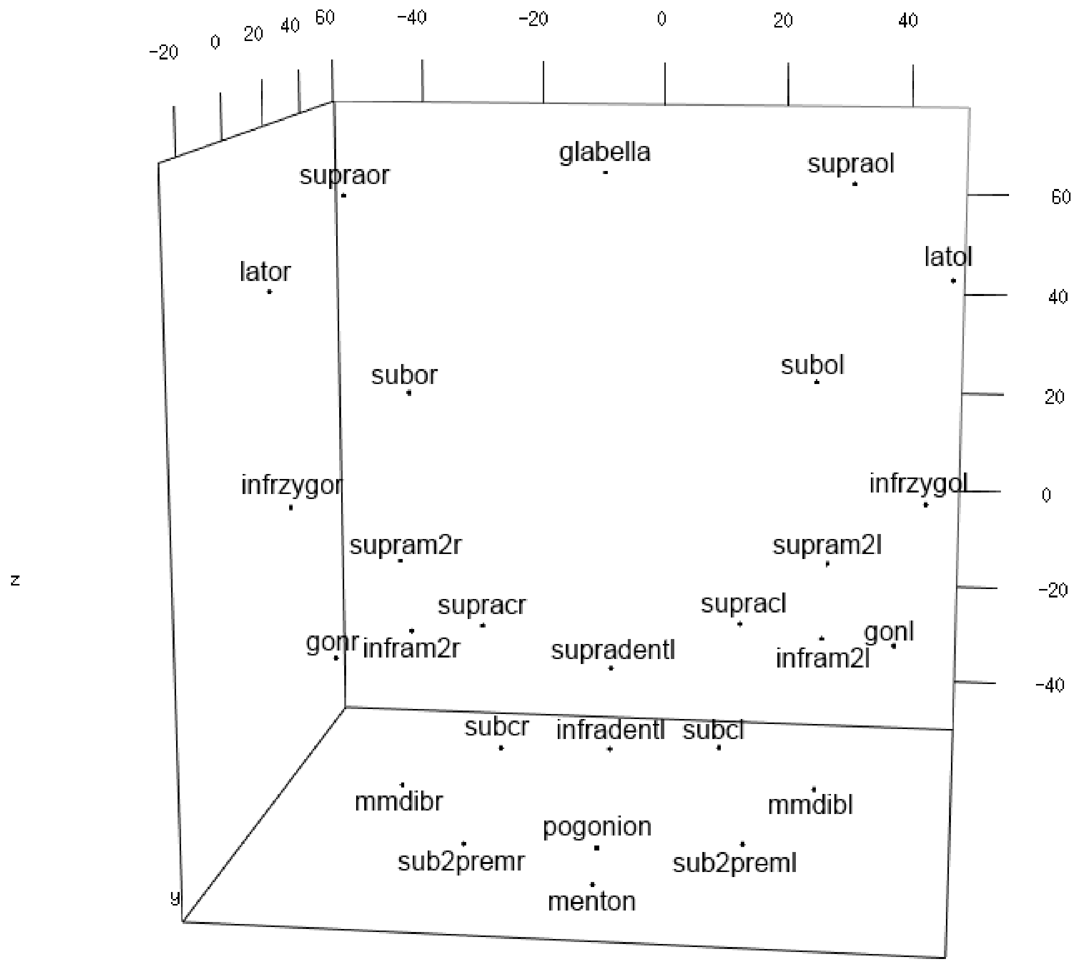

Figure 5: Skull landmarks used in the reconstruction.

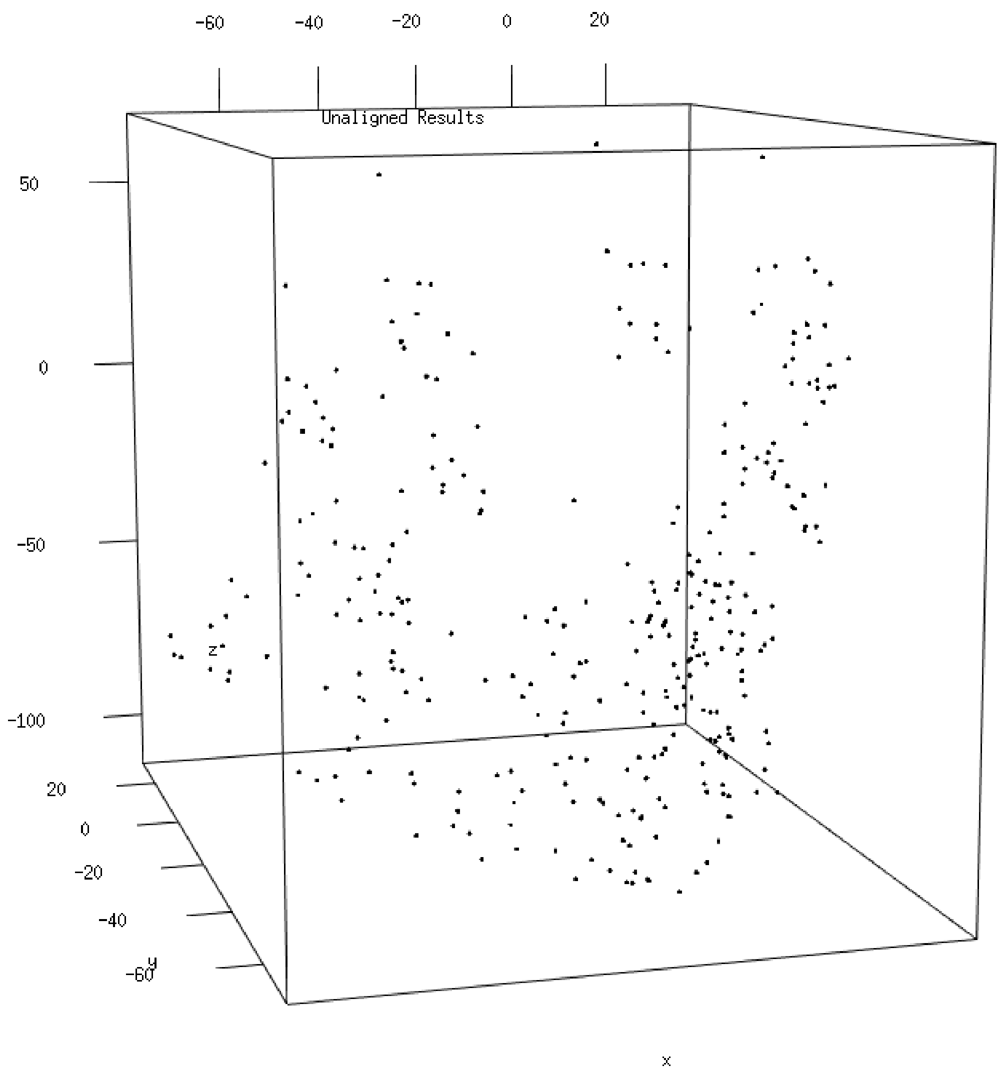

Figure 6: 12 subject's skull landmarks before alignment.

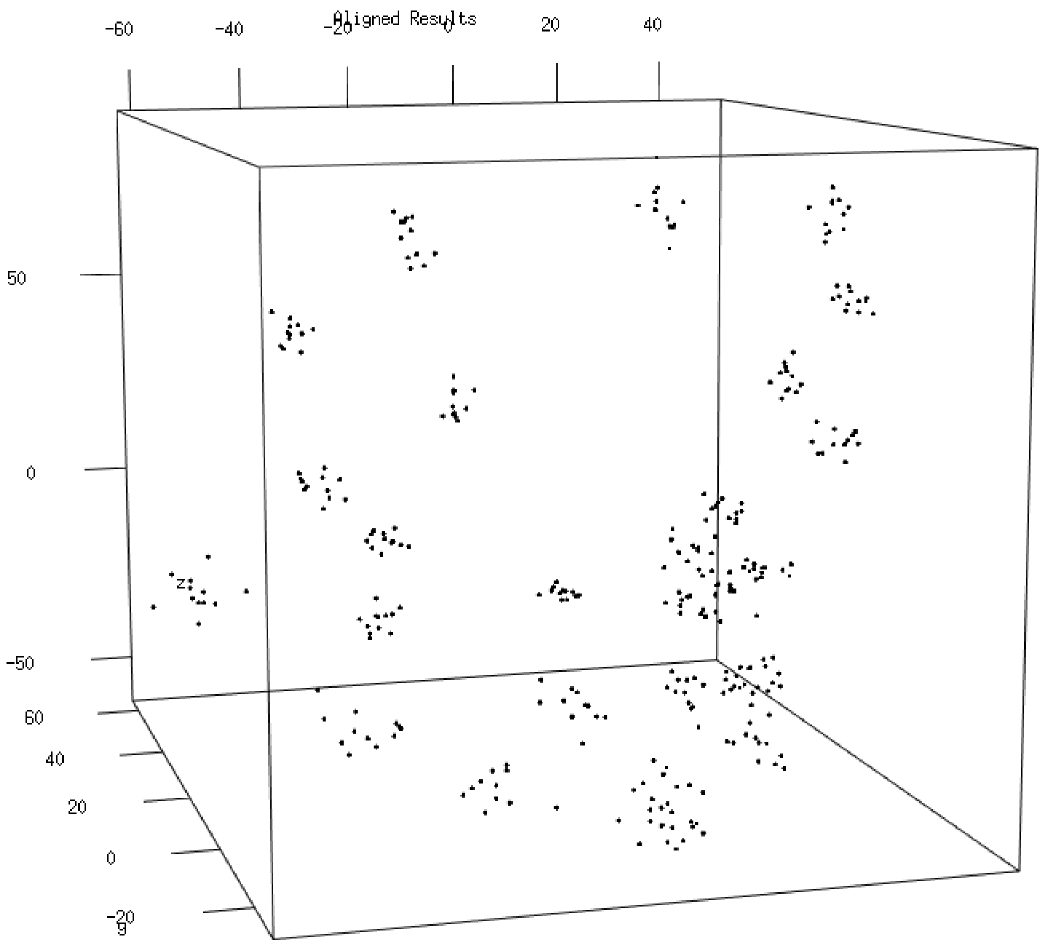

Figure 7: 12 subject's skull landmarks after alignment.

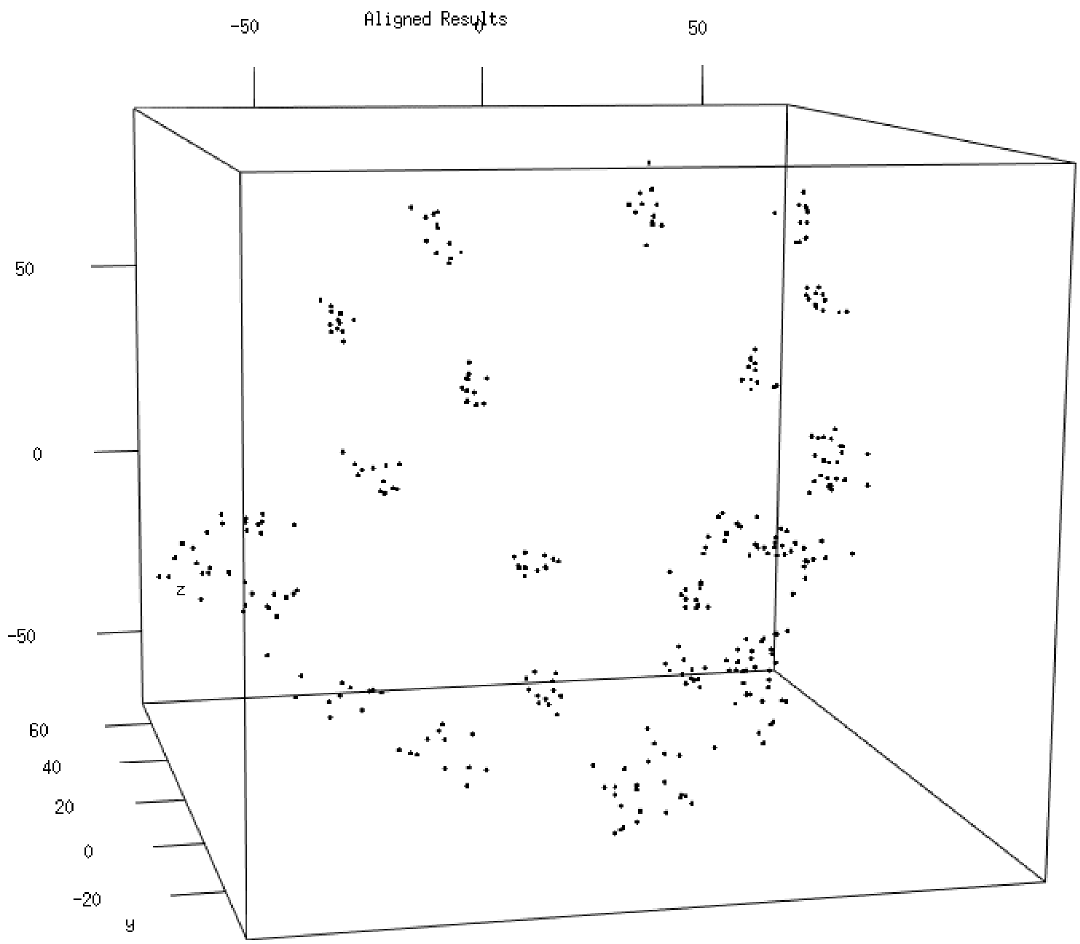

Figure 8: 12 subject's skin landmarks after alignment.