Course Work Cover Sheet - the School of Computing

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Signed: Kyle harrison

LAND MARKING A FACE DATA SET

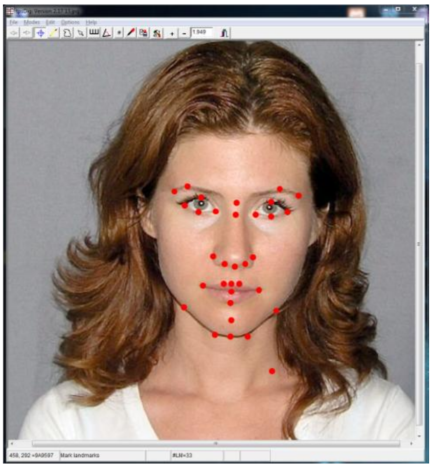
The initial task of land marking a number of mug shots demonstrated how using a manual land marking process can be tedious, lengthy, and error prone for a number of reasons. The dataset provided demonstrates a range of flaws such as some land marks being excluded regardless of how the photograph is taken due to features such as hair, facial hair, or glasses blocking land mark positions.

At this point transformation, scale, and rotation has not been preformed and this is reflected in the dataset as the dataset varies in how the photograph is taken for each mug shot. The following images show how applying transformation, scale, and rotation at this early stage would improve the land marking process as it appears each image has been captured in a different way. Ideally a dataset would be captured in a controlled environment to minimise these problems.

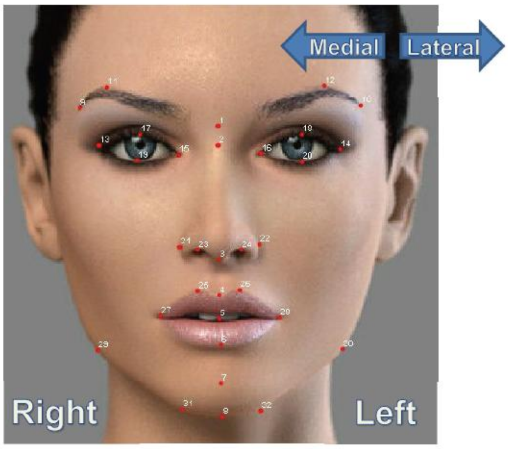
Additionally, some landmarks are difficult to place based upon other factors such as lack of defining features. Brian Hugh Warner, otherwise known as Marilyn Manson is a key example of this as the most lateral point and highest point on the upper margin of both the left and right eyebrows cannot be placed reliably.

Identifying a specific point on mug shots according to a set of rules initially appears to be a simple task as the example guide on how to place landmarks, demonstrates how to do this on a perfect example of how landmarks could be placed correctly. However in the mugshot dataset. even when all land marks are clearly visible and easily identified, errors still occurred such as additional landmarks being placed. For example, in the image of Anna Chapman, it can be seen an additional land mark has been placed resulting in an error inside the .TPS file creating problems and resulting in the homology not longer being valid.

Images 1 : Land marking images



Anna Chapman landmarks



Example landmarks

Images 2 : Mug shots

Demonstrating the effect of Transformation , Scale, and Rotation would have on improving the accuracy of the land marking process.

Bill Gates : Image Scaled however land marks are excluded due to hair and glasses.

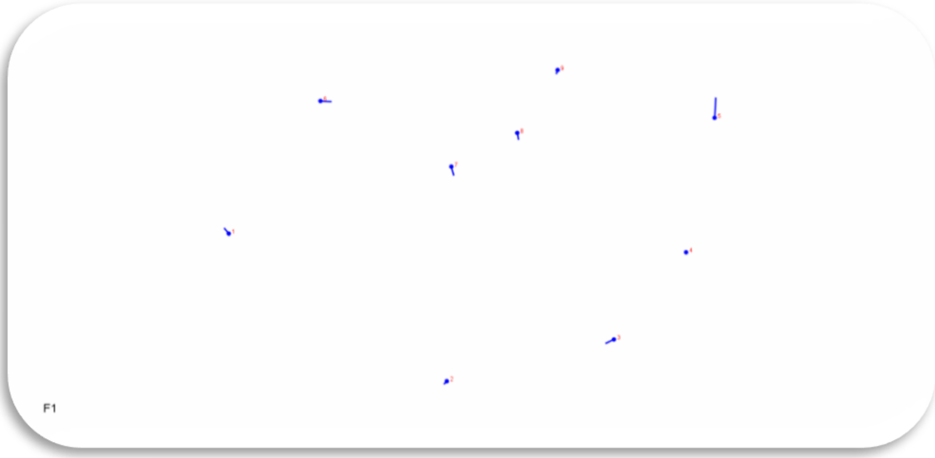
Paris Hilton : Image rotated but angle causes most lateral point of the right eyebrow to become difficult to landmark.

Marilyn Manson : Lack of distinguishing features makes it difficult to place landmarks for the most lateral point of the eyebrows and highest point of the upper margin of the eyebrows.

Analysis of Hand Shape in 2D

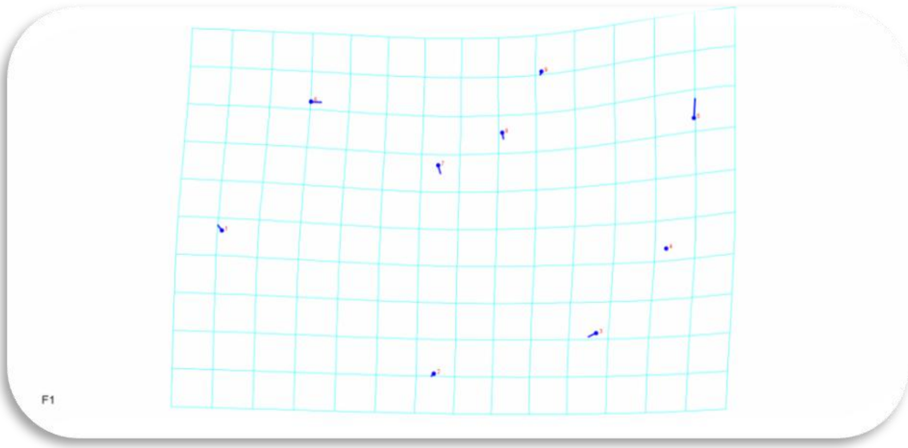
We can't visualise more than 3 of the dimensions however each point in the space generates a different shape generated from contours from landmarks by interpolation. By finding the mean shape using Principal component analysis (PCA) we can create as many dimensions as we desire however after typically 5-10 the variance decreases to an insignificant amount and can easily be confused with noise. Identifying the direction of the largest variance is "Principal component" one. What runs orthogonal to it is Principal component 2. In this section I will demonstrate how the principal components can show the variance in hands using the same hand and even how to determine the gender of a hand.

Image 3 : Hands Lollipop Graph



The lollipop graph is difficult to interoperate without a wireframe however it does identify points with the most variance. An understanding of the data suggests these points with the most variance are the position of little finger tip, the spread between the thumb & index finger, the index finger & the middle finger, the spread between middle finger & ring finder, and lastly the position of the tip of the thumb.

Image 4 : Hands Transformation Grid



The transformation grid can be used to help measure depth and how a hand deforms the space around it. Using this depth the data could be recreated in a simple experiment that utilises an optical illusion to create the illusion of a real hand in 3D space using land marks and transformation grid. [1]

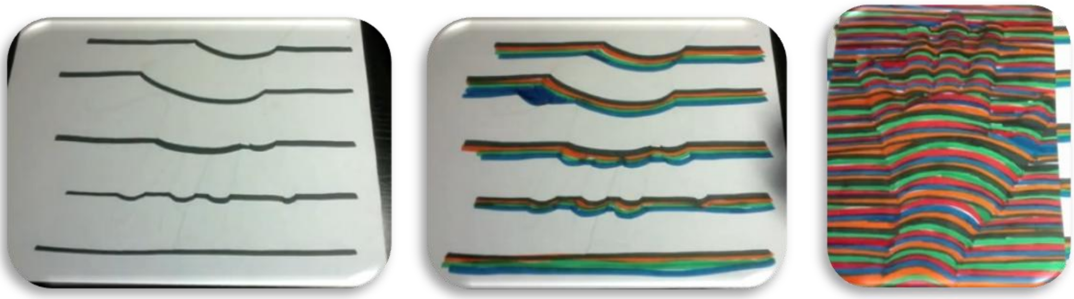
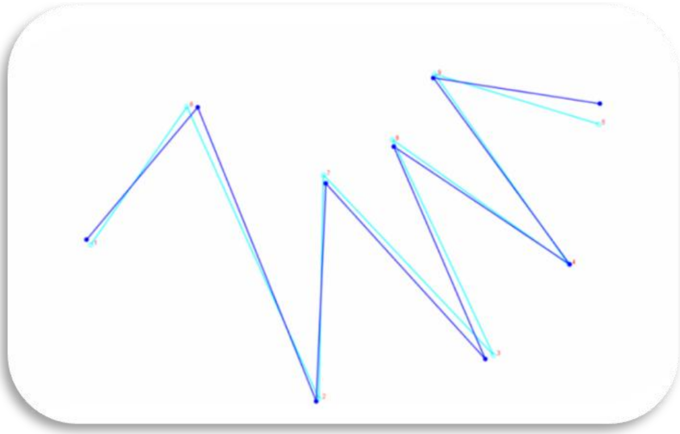


Image 5 : Hands wire Frame



[1]

Reconstructing the data points from the wire frame using my own hand we can see that the variance in the two hands is that one has a wider spread than the other. Hand image 1 demonstrates the dark blue wireframe whilst hand image 2 demonstrates the light blue hand.

Hand Image 1

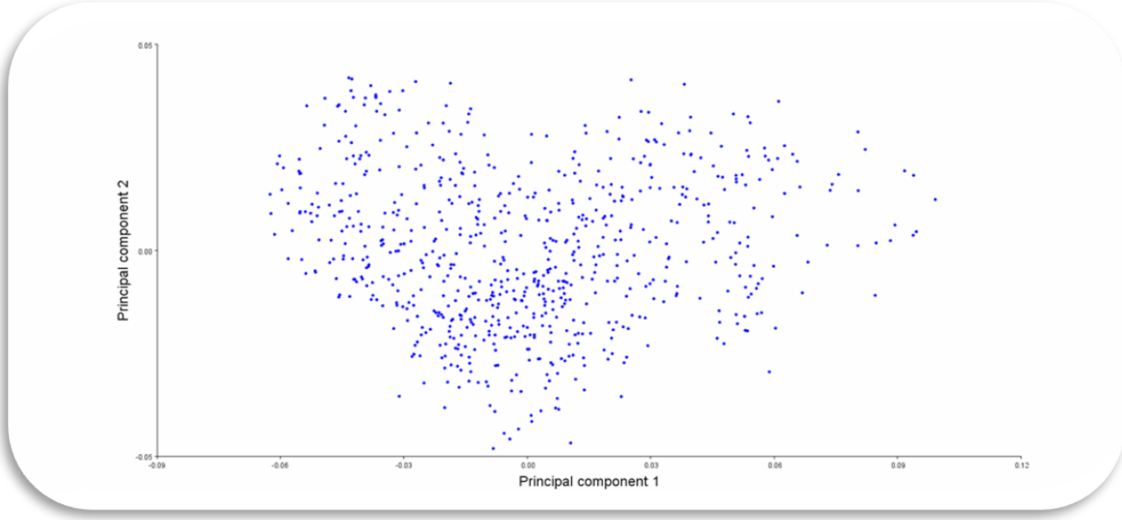
Hand Image 2

[1] *Draw a 3D hand optical illusion - Published on 27 November 2013*, viewed 3 February 2014, < http://www.youtube.com/watch?v=VbT6KVSbCT4>.

Hand 1 shows a slightly wider spread between the index and middle finger, and the thumb is spread out slightly further. Meanwhile the ring finger remains stationary and the little finger spreads out further. Hand 2 shows less of a spread between the thumb and the hand, the index and middle finger are closer together, the ring finger is still in the same location, and the little finger is closer to the ring finger.

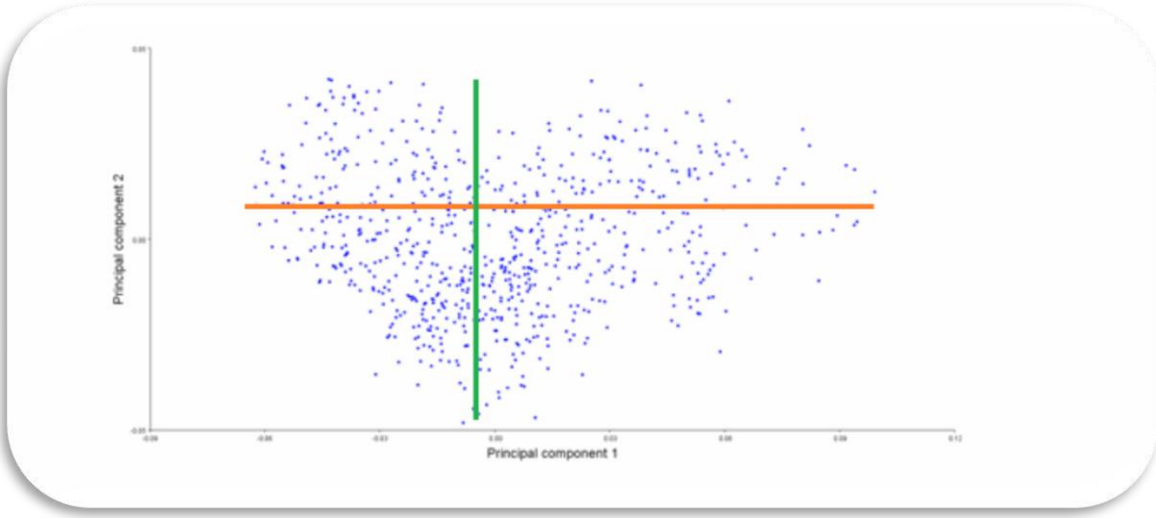
From the mean location between these two hands if you were to follow the variation in one direction the fingers would be spreading with the exception of the ring finger, whilst the other direction would show the fingers moving inwards with the exception of the ring finger which would remain in a constant position in both.

Image 7 : Principal components 1 vs. principal components 2



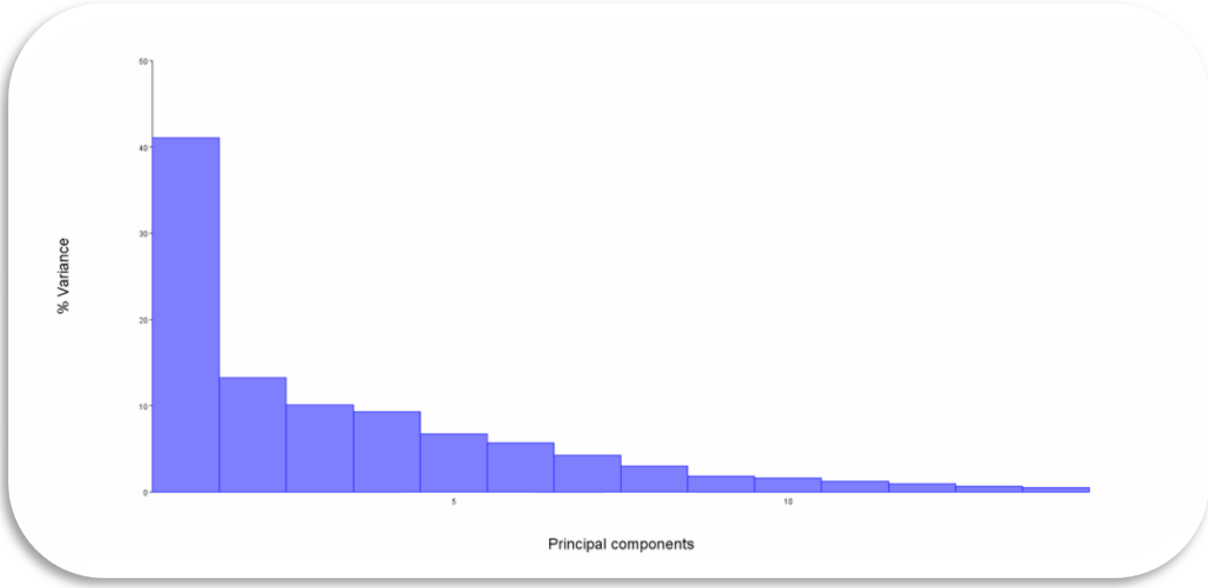
PC1 and PC2 have been generated by MorphoJ but to better understand the variance between the two the following graph shows clearly where PC1 and PC2 lye within the data.

Image 8 : Identifying PC1 and PC2



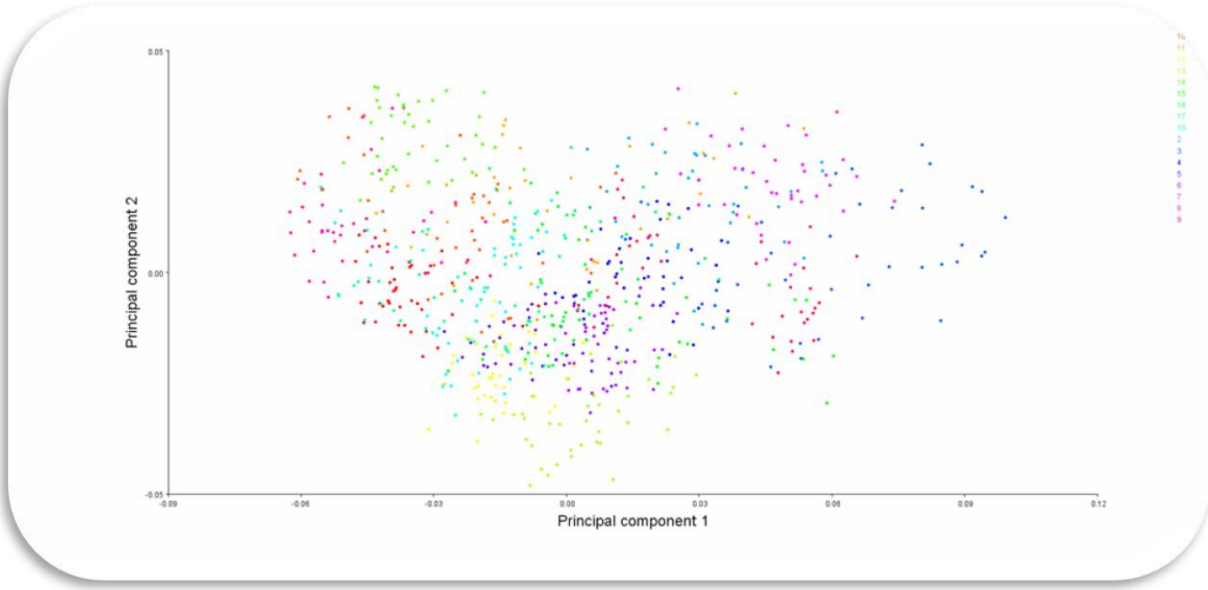
Principal component 1 can be identified by the orange horizontal line and principal component 2 is orthogonal to this running horizontally and can be identified by the green line. This shows the maximum variance in hands with PC1representing a approx 41% of the total variance. PC2 represents approx 14% of the of the total variance.

Image 6 : Eigenvalues of hands



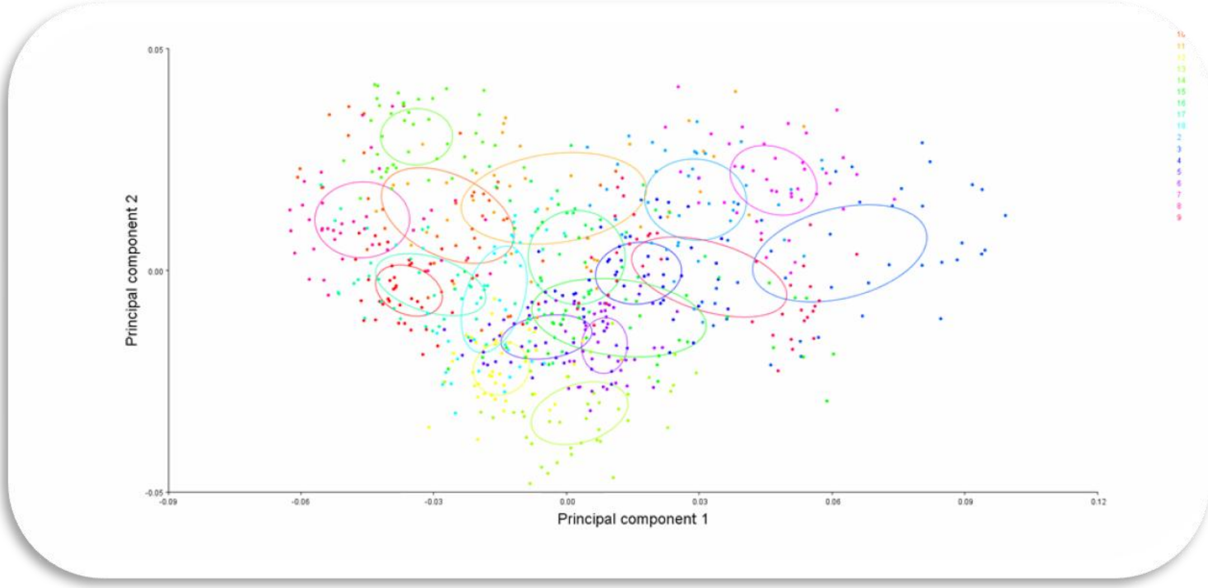
The Eigen values can be seen in the following graph. PC1 can clearly be identified as holding the maximum variance at a little over 40% and PC2 is second at 14%

Image 8 : Principal components 1 vs principal components 2 - Individuals



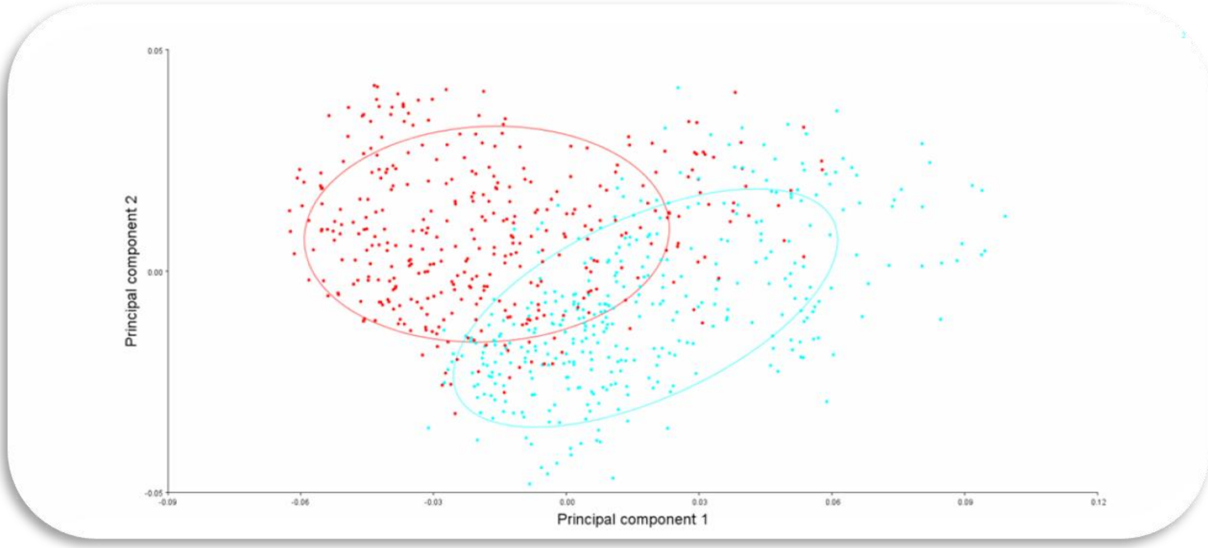
Colouring the data by individual does not clearly allow for predictions to be made regarding what a single individuals hands will look like.

Image 9 : Equal Frequency confidence ellipses for individuals



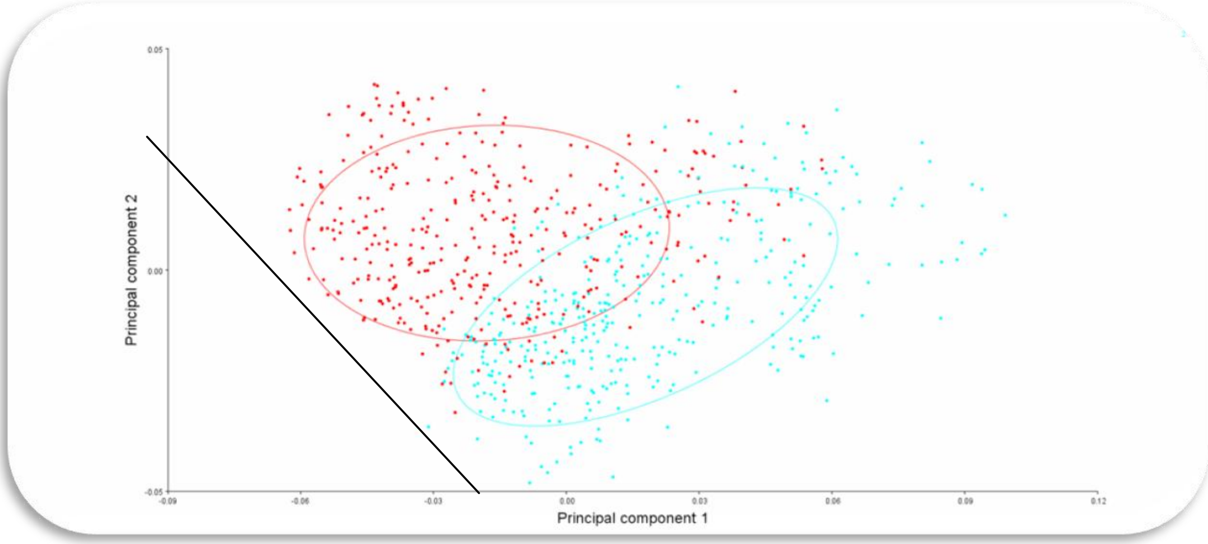
When ellipses are applied to individuals using the equal frequency confidence ellipses data still cannot be reliably gathered for individuals. The ellipses simples infers roughly where the individuals hands may be. The majority of the time a users hands are too wide spread to confidently predict where they may be.

Image 10 : Equal frequency confidence ellipses for gender



However gender is an excellent indicator for identifying the gender of an individual by their hands. With a large degree of accuracy you can successfully identify male and female hands from their confidence ellipses.

Image 11 : Equally Frequency confidence ellipses for Gender vs. CVA

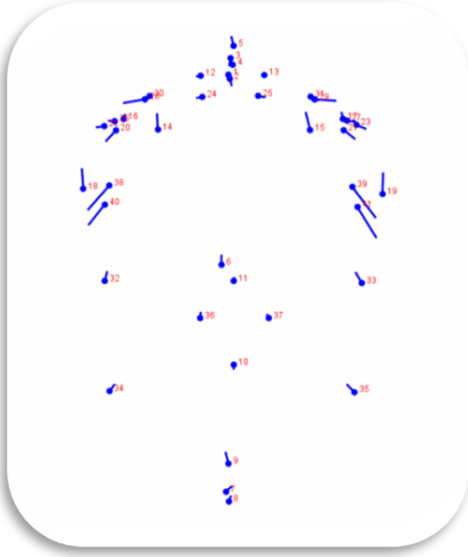


Canonical variant analysis (CVA) would provide an excellent indicator for allowing an individual's gender to be determined by their hands. The diagonal line in the graph above would be used in place of PCA and a result like the following would be produced.

Although there is some overlap, with a greater degree of accuracy the gender of an individual could be predicted. As the hands move towards the left of the graph the degree of accuracy of determine they are female hands increases. Vice versa, then the hands move towards the right side of the line they probability of being male hands increases.

Analysis of Skull Shape in 3D

In this graph it shows that the forehead is increasing upwards becoming elongated whilst the chin and jaw line are moving outwards. I assume this graph was the front face of the skull as it appears to have multiple land marks around the key areas where the nose, chin, and plates of bone connect in the head .



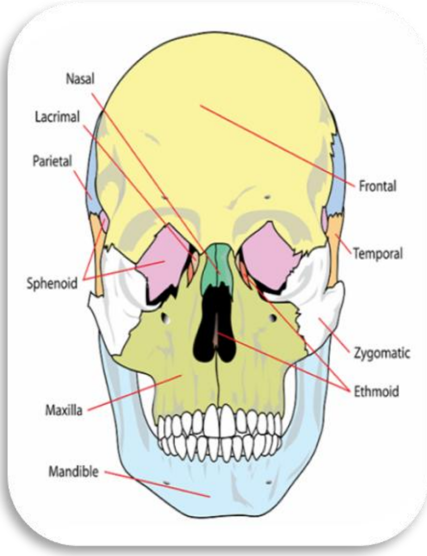
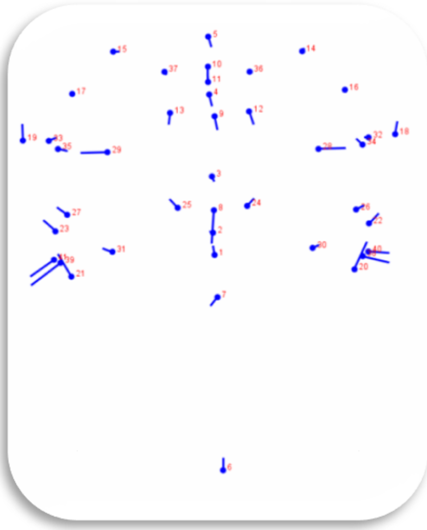
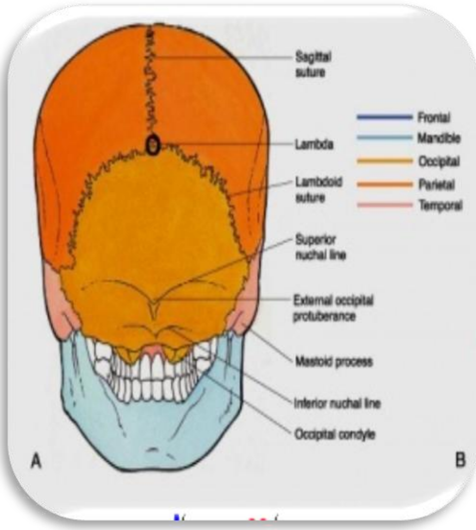


Image of Lollipop graph for skull front

My assumption suggests that this is the back of the skull as the land marks around the left and right side of the top of the skull confirm the suspicion that the back of the skull containing is increasing in size. The land marks also suggest relation to the Sagittal, lambda. lambdoid, superior nuchal line, external occipital protuberance, mastoid process, interior nuchal line, and occiptal condyte to confirm this.





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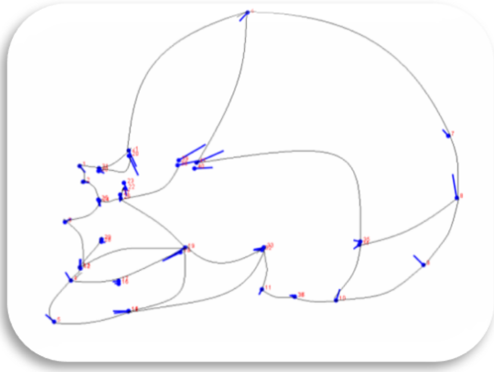
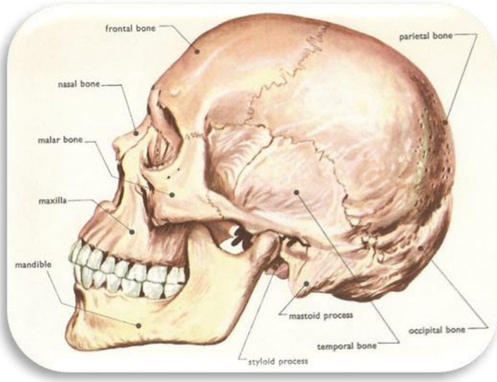
[22] http://www.rahulgladwin.com/medimages/plog-content/images/free-usmle-medical-images/skull-vessels/skull-back.jpg

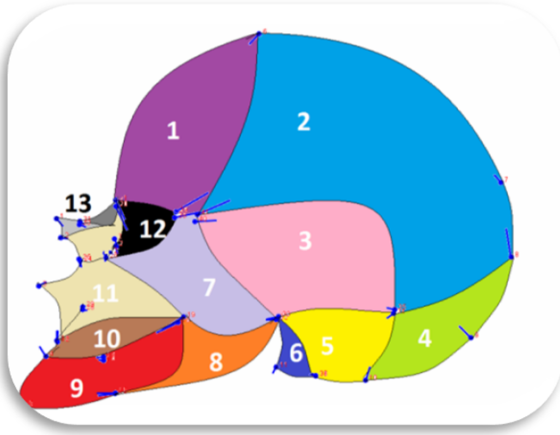
Image : Side view of Skull

The lollipop graph shows the vague outline of the skull shape however the wireframe tool did not seem appropriate for modelling the skull due to the intense angels at which the points were connected. Using Microsoft paint and the curve tool, with some imagination the skull becomes slightly more realistic. Although the points where connected up in a "best guess" combination from what I could identify on other skull images it appears to have identified key portions of the skull and the connecting plates of bone.





1. Frontal Bone
2. Parietal Bone
3. Temporal Bone
4. Occipital bone
5. Mastoid Process
6. Styloid Process
7. Malar Bone
8. Mandible
9. Mandible
10. Teeth
11. Maxilla
12. Eye Socket
13. Nasal Bone



http://pixabay.com/static/uploads/photo/2012/04/25/01/09/diagram-41552_640.png

Image of Eigan Values

The Eigen values show that Principal component one contributes to almost 14% of the maximum variance followed closely by Principal component 2 at approx 11%. From viewing the lollipop graph it appears that principal component one is the parietal bone downwards and the temporal bone outwards. The eye sockets also increase by moving forward and the mandible extends forward.

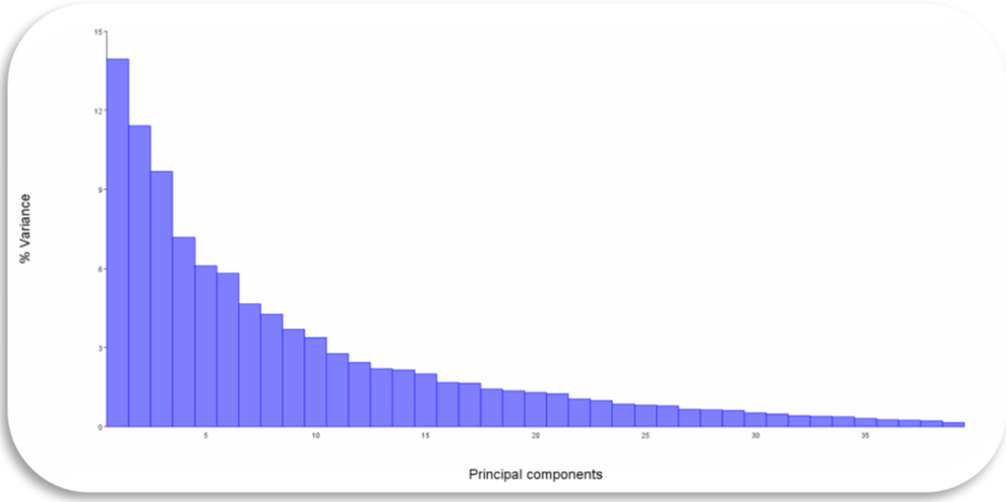
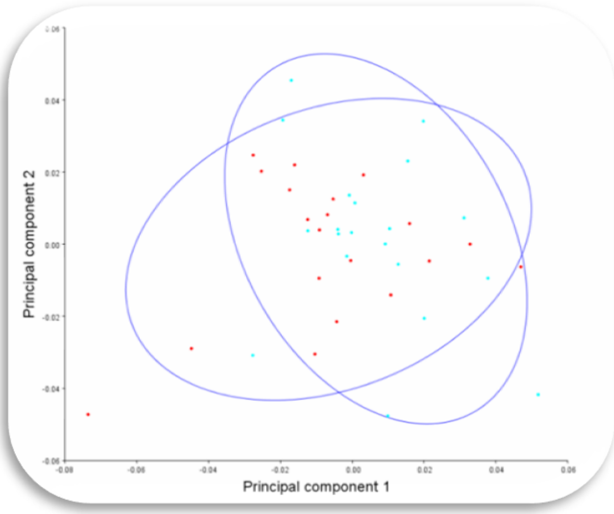


Image of Principal components for Skull

When comparing the principal components of the data using the sex as an identifier and using confidence ellipses it can be seen that gender cannot be inferred from this data set due to the large overlap of the data.



With a greater understanding of forensics it may be possible to determine the sex of an adult from this data using the Orbital form, mandibular flexure, and sciatic notch presented in this data set however this is beyond my understanding. From lecture slides it appears that additional landmarks would be required in order to do this and expertise in the area.