Human Ovulation Hidden Hints and It’s Effects on Fluctuant Assymetry Studies

Mahsa Kiazadeh¹, Gabriela Goncalves² and Hamid Reza Shahbazi³

¹DEEI, FCT Universidade de Algarve, Faro, Portugal
²Departamento de Psicologia e Ciencias de Educacao, Universidade do Algarve, Faro, Portugal
³SAS, University of Central Asia Naryn Campus, Naryn, Kyrgyzstan

Keywords: Facial Landmarks, Human Ovulation, Fluctuant Asymmetry, Facial Features, Attractiveness.

Abstract: This document tries to study the truth about human concealed ovulation only by analysing possible facial modifications. In normal view, the human ovulation remains concealed. In other words, there is no visible external sign of the mensal period in humans. These external signs are very much visible in many animals such as baboons, dogs or elephants. Some are visual (baboons) and others are biochemical (dogs). Insects use pheromones and other animals can use sounds to inform the partners of their fertility period. The objective is not just to study the visual female ovulation signs but also to understand and explain automatic image processing methods which could be used to extract precise landmarks from the facial pictures. This could later be applied to the studies of fluctuant asymmetry. The field of fluctuant asymmetry is a growing field in evolutionary biology but cannot be easily developed because of the time necessary to extract landmarks manually. In this work we have tried to see if such signs are present in human face during the ovulation could be detected, either by computer vision or by human observers. We have taken photography from 50 girls for 32 days. Each day we took many photos. At the end we chose a set of 600 photos, 15 photos per girl representing the whole mensal cycle of 40 women. The photos were organized in a rating software to allow human raters to watch and choose the 2 best looking pictures for each girl. These results were then checked to highlight the relation between chosen photos and ovulation period in the cycle. The results, were indicating that in fact there are some clues in the face of human which could eventually give a hint about their ovulation. Later, different automatic landmark detection methods were applied to the pictures to detect landmarks which could show the changes in the face during the period. Although the precision of methods tested are far from being perfect, but the comparison of these measurements to the state of art indexes of beauty shows a slight modification of the face towards a prettier face during the ovulation. The automatic methods tested were Active Appearance Model (AAM), the neural deep learning and the regression trees. It was observed that for this kind of applications the best method was the regression trees. Future work has to be conducted to firmly confirm these data, number of human raters should be augmented and a proper learning data base should be developed to allow a learning process specific to this problematic. We also think that low level image processing will be necessary to achieve the final precision which could reveal more details of possible changes in human faces.

1 INTRODUCTION

The capacity of a living organism genotype to create a perfect symmetry in the final form of individuals is believed by biologists to be a sign of genetic quality. In other words a better symmetry means a better genotype.

It is therefore normal that a lot of work and studies concentrate on understanding the links between this symmetry in the phenotype and the genotype.

Possible links between facial asymmetry and predisposition to some genetic alterations or diseases is an important issue of such studies. A very large interval of research is possible. Sexual attraction passing by genetic illness or mental disorder possible links with visual facial clues are some examples.

Fluctuating asymmetry is a particular form of biological asymmetry, characterized by small random deviations from perfect symmetry. The fundamental basis for the study of fluctuating asymmetry is an a
priori expectation that symmetry is the ideal state of bilaterally paired traits.

Concealed ovulation or hidden oestrus in a species is the lack of any perceivable change in an adult female (for instance, a change in appearance or scent) when she is "in heat" and near ovulation. Some examples of such changes are swelling and redness of the genitalia in baboons and bonobos Pan Paniscus, and pheromone release in the feline family. In contrast, the females of humans and a few other species (Sandy 1987, Brewis 2005) have few external signs of fecundity, making it difficult for the male to consciously deduce, by means of external signs only, whether or not a female is near ovulation.

Nevertheless, the idea of a completely hidden and sign-less period of fertility sounds contradictory to normal rules of re-productivity and mate selection. Some recent studies using fine-tuned phenotype measurements have revealed that some signs appear at the fertile point of the cycle to make the female more attractive to male (Pipitone 2008). Studies over body scent, voice frequency. Soft tissue symmetry, body ratio, creativity and fluidity in speech and facial attractiveness were assessed and studied as possible modifications that alerts a male over the fecundity of the female (Geoffrey 2007). Some other studies over the amount of tips gained by lap dancers in different period of their mensal cycle shows that the dancers earned much more during the oestrus or just before ovulation.

As one can see through these studies that hearing, smell and sight could all be used to receive fertility signs, but the human society defines attractiveness solely by means of sight. Therefore, if signs of oestrus do exist between human, they should mostly be present in visual clues. In this paper we focus on facial attractiveness during the cycle. The previous study on the subject have revealed possible signs but in a very limited proportion, Roberts & al used only 2 photos of women one in follicular phase and one in lethal phase to distinguish between possible visual cues. The results obtained by Roberts & al were just a bit over the random of 0.5 expected. The authors recognize also that their study could only suggest a fluctuant facial attractiveness during the mensal cycle.

Now what this facial asymmetry has to do with the topic of this work? Well, the problem of manual analysis is only one aspect that prohibits the verification of different theories on this field. Another point of discussion between some communities lays on the fact that most evolutionary biologists consider that the final form of an individual is achieved after the puberty and this form does not change in short period of time. Therefore, most of the studies over the face asymmetry is done by working only over one picture of the individual. The proponents of this work think that this is not the case. Studying one picture of an individual taken in a particular moment can introduce a lot of bias into the final study of the facial signs and their links to other abnormalities.

This single picture is not really the best way to study possible life term links between phenotype and genotype. To demonstrate and prove that individual faces can show minor differences even in short term, the proponents of this study have searched a special case of physiological changes in human body in short terms that may affect the facial form.

The best and straight forward case in human of a deep physiological change in a short period of time is the mensal cycle in women. This fix periodical physiological change modifies deeply the biochemical composition in the body by modification of different levels of hormones. The fact of the periodicity of this phenomenon is also a positive point because it allows the total repeatability of the study whenever necessary. If a facial modification during the mensal period is proved and formally calculated, then it is clear that most studies over links between facial symmetry and genotype abnormalities are to be repeated as they are only based on single photography.

2 DATA COLLECTION AND METHODS

As the idea was to test and gather data over a mensal period and that there is no such database available, we had to start first by gathering the necessary data. The data needed to be collected over a whole period and each day the women who participated in the experience had to come to the lab to take a picture in particular setting.

Once the data was collected we needed first to prove that there is a perceptible change in the visual aspects of the face. Therefore, human raters had to rate the pictures of the same woman over her mensal period. A simple analysis of the results could give a hint that a change occurs during the period and therefore fluctuant asymmetry studies could not take place over a simple photo of one day.

Then we needed to landmark all faces manually to create a ground truth data base for comparison with automatic methods. Finally different automatic landmark extraction methods had to be implemented and tested over our own database.
In the following sections, these steps are explained and some of the preliminary results are presented.

2.1 Data Collection

50 women were photographed for 32 days, about 10 photos each day. From this set of pictures, we have chosen one best photo for each day and for each woman. Then they are normalized as much as possible for light and contrast.

All women were chosen from Portuguese nationality. They were all aged between 20 and 35 and they were all university students. All data about their sexual orientation, partners and contraceptive methods was collected for further analysis. The data base is not yet publicly available as the study is ongoing and legal permissions are not yet obtained.

2.2 Human Rating

The photos were organized in a data base linked with a visual interface. 15 pictures of each woman were chosen to be presented to human for rating. Each rating person had 15 seconds to choose the best 3 photos of the set according to the attractiveness. None of the rating persons knew about the objective of the study and none of them knew any of the women in the data set personally.

The results were stored in data files and checked for consistency manually.

The rating persons were chosen from different nationalities in 2 different countries (Portugal and France). The rating process is time consuming, so, up to now only 130 people have rated the photo data set.

2.3 Manual Landmark Extraction

All photos of the data set were manually tagged, and main facial landmarks were extracted. The manual process was repeated twice to eliminate human mistakes as much as possible. More than 600 photos were manually tagged and stored as a precision data base for facial landmarks. The process is extremely time consuming but allows a proper study over the precise positions of facial traits needed in this study.

2.4 Automatic Landmark Extraction

Facial landmarks are defined as detection and extraction of key-points of the face that will deeply affect the construction or appearance of the face. These landmarks such as nose tip, eyes corners, chin, mouth, lips etc. will define a particular semantics of a given face. Many technics of facial landmark detection are available, and the subject has been studied for many years. The facial traits play an important role in recognition, identification, expression tracking, animation or 3D construction.

In this study we have tried and implemented regression trees, active appearance models and deep learning CNN.

2.4.1 Regression Trees

The detection is based on OpenCV and dlib (http://dlib.net/) library. The pre-trained landmark detection model is used to detect facial landmarks. Two landmark detection models are tested, and results will be provided: a) 68 facial landmarks and b) 194 facial landmarks. This dlib’s face key-point detection implementation is based upon “One millisecond face alignment with an ensemble of regression trees.

One millisecond face alignment (Kazemi 2014) with an ensemble of regression trees: In this method an ensemble of regression trees can be used to estimate the face’s landmark positions directly from a sparse subset of intensities, achieving super-real-time performance with high quality predictions. An ensemble of regression trees is learnt based on gradient boosting optimizing the sum of square error loss and naturally handling the missing or partially labelled data (Federico 2012).

The algorithm works as follows. Let $x_i \in \mathbb{R}^2$ be the $x,y$-coordinates of the $i$th facial landmark in an image $I$. Then the vector $S = (x_1^T, x_2^T, ..., x_p^T)$ denotes the coordinates of the $p$ facial landmarks in $I$.

We refer vector $S$ as shape and $\hat{S}(t)$ denotes current estimate of $S$. In each stage, each regressor $r^{(t)}$ in the cascade predicts an update vector from the image and previous estimate, which can be denotes as follows:

$$\hat{S}_{t+1} = \hat{S}_t + r_t(I, \hat{S}_t) \quad (1)$$
2.4.2 Active Appearance Model

Facial landmark point extraction is a key step in facial image representation and analysis. The Active Appearance Model (AAM) proposed by Cootes et al (Cootes, 1998), is a powerful object description method that is commonly used for facial landmark points extraction. AAM fitting is a non-linear optimization problem. Different optimization approaches have been proposed to find the best model parameters that result in minimum error between the synthesized appearance models obtained from the AAM and the input image. In general, due to variation of camera view angle, resolution and focal distance, facial images have different scaling, rotation, and translations. In order to remove global shape variations, all shapes are normalized and the modelling is only concerned with local shape deformation. Therefore, it is necessary to combine a global shape transformation with the normalized AAM. The global shape transformation is often a 2D similarity transformation. Finding optimal parameters of the global transformation improves the accuracy of fitting in representing novel facial images with different shape and pose variations.

Traditionally, the stochastic gradient descent algorithm or iteratively incremental additive techniques are used to update the AAM parameters to fit onto novel images. The fitting problem can also be viewed as finding a model instance similar to the given facial image and therefore it can be considered as an image alignment problem.

**Algorithm 1: demonstration of the learning rate in the cascade.** (Dantone 2012, Xiangxin 2012).

1. Initialise

\[ f_0 (l, \hat{S}^{(t)}) = \arg\min_{y \in \mathbb{R}^p} \sum_{i=1}^{N} \| \Delta S_i^{(t)} - y \| ^2 \]

2. For \( k = 1, ..., K \):
   
   (a) Set for \( i = 1, ..., N \)

   \[ r_{ik} = \Delta S_i^{(t)} - f_{k-1} (l_{ni}, S_1^{(t)}) \]

   (b) Fit a regression tree to the targets \( r_{ik} \) giving a weak regression function \( g_k (l, S^{(t)}) \)

   (c) Update

   \[ f_k (l, S^{(t)}) = f_{k-1} (l, S^{(t)}) + \nu g_k (l, S^{(t)}) \]

3. Output \( r_k (l, S^{(t)}) = f_k (l, S^{(t)}) \)

AAM consists of a shape component and an appearance component obtained from a set of annotated landmark points in training images. Let’s assume we are given a training facial image set with annotated shapes defined as: \( \hat{S} = (X_1, Y_1, X_2, Y_2, ..., X_v, Y_v) \) (Geoffrey Miller, 2007). The training images are first normalized and aligned using iterative analysis. This step removes variations due to a chosen global transformation.
shape normalization transformation so that the resulting model can efficiently consider local and non-rigid shape deformation. We then can combine the resulting AAM with a global transformation. Afterwards, Principal Component Analysis (PCA) is applied to the set of normalized training shapes and a shape model is defined as:

$$ S = S_0 + \sum_{i=1}^{n} p_i s_i , \quad (2) $$

Where the base shape $S_0$ is the mean shape and the vectors $S_i$ are $n$ eigenvectors corresponding to the $n$ largest eigenvalues. Then, all the training images are normalized by warping them into the base shape $S_0$, using piecewise affine warp, and the appearance model is defined as:

$$ A(x) = A_0(x) + \sum_{i=1}^{m} \lambda_i A_i(x) \quad \forall x \in s_0 , \quad (3) $$

Where $A_0$ is the mean appearance and the vectors $A_i$ are the $m$ eigenvectors corresponding to the $m$ largest eigenvalues. The goal of fitting is to find a model instance that can efficiently describe the object (e.g. face) in a given image. Thus, it can be considered as an image alignment problem. In other words, we want to find the model instance $M(W(x; p)) = A(x)$ as similar as the image $I(x)$. In general, facial images have different scaling, rotation, and translations. Therefore, it is necessary to combine a global shape transformation with the normalized AAM. If we consider the global shape transformation as $N(x; q)$, we want to minimize the error between the template and $I(N(W(x; p) ; q))$. Considering global shape transformation, the objective of the fitting process is to find $p$ and $q$ in order to minimize the error image as:

$$ E(x) = \sum_{x \in s_0} [A_0(X) - I(N(W(x; p); q))]^2 , \quad (4) $$

Which is a non-linear least square problem. We can have different definitions for the global transformation $N(x; q)$. (Matthews 2004) a set of 2D similarity transformations as a subset of piecewise affine warps is defined. This representation of $N(x; q)$ is similar to $W(x; p)$ and therefore similar analysis on the shape parameters $p$ can be applied to $q$. If we assume that the two sets of shape vectors $S_i$ and $S_i^*$ are orthogonal to each other, we can add the four 2D similarity vectors $S_i^*$ to the beginning of AAM shape vectors $S_i$ (Matthews 2004) and model any given shape as: $s = s_0 + \sum_{i=1}^{n+4} p_i s_i$. In practice, $S_i$ and $S_i^*$ are not quite orthogonal to each other. This can either be ignored when the size of $S_i$ is small or the complete set of $S_i$ and $S_i^*$ can be orthonormalized preferably.

In (Baker 2004) Baker et al. relate AAM to the Lucas-Kanade algorithm. They proposed the Inverse Compositional Algorithm (ICA), in which they find shape variation on the template and compose the inverse of that with the current shape. Therefore, many computationally expensive tasks are recomputed. Appearance variation is considered in the fitting by finding shape parameters in a linear subspace where the appearance variation is ignored and then “projecting out” to the full space with respect to the appearance eigenvectors (Matthews 2004). The method is more generic compared with the ICA, but the fitting is not accurate when applied to subjects that are not similar to subjects in the training set. The “projecting out” approach is called PO in the rest of this paper. Simultaneously Inverse Compositional (SIC) method (Gross 2005) is introduced, which is more generic. In this method the fitting procedure minimizes the error between $[A_0(x) + \sum_{i=1}^{m} (\lambda_i + \Delta\lambda_i) A_i]$ and $I(N(W(x; p); q))$, where $\lambda_i$ are appearance eigenvectors correspond to the $m$ largest appearance eigenvalues, and $(\lambda_i + \Delta\lambda_i)$ are parameters of appearance that are found simultaneously with respect to $\Delta p$. As the appearance parameters are optimized in each iteration, both steepest descent and the Hessian matrix ($H$) should be calculated in each iteration, and therefore the method is slower. The PO (Gross 2005) is compared with the SIC, and the SIC is reported more accurate in modelling unseen subjects.

2.4.3 Convolutional Neural Networks, Deep Learning

Deep learning models have demonstrated impressive performance for different computer vision applications. The deep convolutional neural network (CNN) can map raw data from a manifold to the Euclidean space, in which features may be linearly separable. Generally speaking, there are two ways to extract features with deep CNN models. The first way is to extract features on an image pyramid obtained by using object proposals generation methods (such as Selective Search, Edge boxes and CM) or the
sliding-window strategy (such as R-CNN and DenseNet). However, this way suffers from high computational burden. The second way is to obtain features by using the sliding-window strategy on convolutional feature maps (such as OverFeat and faster R-CNN). The second way is usually more efficient to obtain features than the first way, when the sliding-window moves at each position. However, one problem for the second method is that the obtained features are less discriminative than those obtained by the first method. In addition, the computational complexity of both ways is high for object detection.

We have used the CNN structure of (Zhang 2014) with resolution reduction. The fact that the resolution has to be reduced makes the results coarse and the position precision is affected.

Figure 5: Some examples of CNN.

Figure 6: main symmetric axis, tangents to eye iris.

Figure 7: CNN structure.
3 RESULTS

In this section the results are presented in different categories. The first and the most astonishing results are from the human rating process of photos of the same girl during the mensal period.

We divided the mensal period into 3 parts with day distances from the ovulation day. For example, if the ovulation date was 15 of November and the period time was 28 days, then the division was from day 1 to 5 and day 23 to 28 in one group, day 5 to 9 and 18 to 23 in second group and day 9 to 14 and 14 to 18 in the third group.

As the following charts show, a huge majority of rating people chose the attractive photo in the period 9 to 18. This means that majority of people find that photos in the range of 4 days before and after the ovulation time are the most attractive.

This result has a very high impact as it is the first medium scale study showing that human ovulation is not completely concealed.

The impact of this first phase of the study is of importance to any evolutionary biologist or people working with fluctuant asymmetry. No previous study proved the existence of visual clues of human ovulation and a change in visual landmarks. The studies of fluctuant asymmetry should also now be taken with more attention as we proved that human facial clues can have very quick changes and therefore introduce dynamic bias into the final conclusion of asymmetry studies.

The second part of the results shows that the Dlib regression trees provide a better fit over orthogonal pictures with fix gestures, but also demonstrates that for high precision landmark extraction none of the existing supervised learning methods can provide a reliable precision. The authors are developing now low level classic methods for precise extraction of key landmarks with high attractiveness impact to be used for a very precise definition of the affected visual clues. Only few cases of the study are presented here due to data restrictions. All figures are given only over 10 cases randomly chosen among 50 and around 270 rating results.

Presenting the error from the automatic extraction methods is not an easy task when it comes to semantic notion of what is modified. We will use an error given by the sum of difference from some key points to a symmetry axis found by manual tagging (Figure 6) divided by the distance from that axis.

This means that for example if the Dlib error for the left eye is 10%, it means that compared to manual measurements it has a bias of 10% towards the symmetry axis of the face.

![Figure 8: Number of selections in different phases.](image)

<table>
<thead>
<tr>
<th>Methods</th>
<th>Left eye</th>
<th>Right eye</th>
<th>lips</th>
<th>nose</th>
<th>Max bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>DLIB</td>
<td>5.5%</td>
<td>5.6%</td>
<td>4%</td>
<td>9%</td>
<td>5%</td>
</tr>
<tr>
<td>AAM</td>
<td>8.4%</td>
<td>8.8%</td>
<td>4%</td>
<td>8%</td>
<td>8%</td>
</tr>
<tr>
<td>CNN</td>
<td>9.3%</td>
<td>9.1%</td>
<td>4.1%</td>
<td>8%</td>
<td>8%</td>
</tr>
<tr>
<td>PIXEL level</td>
<td>1%</td>
<td>&lt;1%</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>

The maximum bias was obtained by comparing the general symmetries obtained by all 68 points of automatic methods VS the manually extracted symmetry axis.

As mentioned above the Regression trees present a possible choice for huge data sets as the introduced errors are around 5 percent in absolute measures. Never the less the induced changes by physiological modifications are not very large and this small error can still present a huge bias in the final results.

4 CONCLUSIONS

The study carried out has potentially an important impact on different issues. The second phase of this study is concentrated on 2 topics, first one is to fine tune the changes that occur in the mensal period such as nasal area, lips expansion or eye forms and the
second is to create the necessary low level but precise image processing tools to extract the exact landmark point with pixel level precision.

This first phase has showed that visual clues, even very slight modifications can be perceived and interpreted by human as a sign of biological or metabolic modification. If we consider the changes in the nasal area during the time span of a mensal period, then we can see that the studying a face only over one photo obtained in one day cannot be a real tool for any serious asymmetry studies.

If the asymmetry is around 5% for example and that we get a bias of 3% from first day of ovulation to the 14th day then obviously the induced error is far too high to allow any correct conclusion. We have not presented all the conclusions and data in this paper due to ongoing and pending ethical authorizations and data privacy issue. These data will be published as soon as the necessary legal issues are solved.

For one particular case of nose area modification we can see in the following table that this area is very sensitive to physiologic modifications.

ACKNOWLEDGEMENTS

We would like to give all our gratitude to students who participated in the creation of the data base.

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