ANTHROPOLOGIE • XLIX/2 • pp. 141–153 • 2011

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FACIAL IMAGE ANALYSIS IN ANTHROPOLOGY: A REVIEW

ABSTRACT: Faces have recently become the subject of intensive research straddling the disciplines of biological or forensic anthropology, computer science, medical image analysis, statistics, and genetics. Image analysis, as a highly developed discipline of computer science, is not only devoted to applications of information technology to images but also can be described as a scientific discipline aimed at extracting information from images. This paper gives an overview of the methods used to analyse two-dimensional and three-dimensional, images, which are applicable to practical tasks of biological and forensic anthropology. We discuss the role of image pre-processing in computer-assisted methods in anthropological research. An up-to-date overview of the methods of image analysis used for various anthropological tasks is given, including methods of rigid and deformable template matching, geometric morphometrics, and statistical methods suitable for information extraction from images. For inspiration, we pay attention also to remarkable image analysis methods, which have recently been proposed in computer science for the analysis of facial images. Finally, we describe a study of face identification, which compares various approaches to dimension reduction and classification analysis and brings arguments in favour of robust image analysis that is based on robust statistical methodology.

KEY WORDS: Face – Computer-assisted methods – Template matching – Geometric morphometrics – Robust image analysis

INTRODUCTION

Faces have recently become the subject of intensive research straddling the disciplines of biological or forensic anthropology, computer science, medical image analysis, statistics, and genetics. This research allows a quantitative analysis of faces and can be described by the term virtual anthropology (Weber, Bookstein 2011).

The first methods for the automated analysis of faces were proposed by computer scientists with the aim of identifying individuals in two-dimensional (2D) and later also three-dimensional (3D) images. These methods have become the basis for current image analysis methods applicable also to anthropological tasks where faces are objects of research. These tasks include:

- Identification of individuals, e.g., victims of a disaster, crime victims, or perpetrators (Damas *et al.* 2011);
- Facial reconstruction from a skull (in forensic or archeological applications) (Vanezis 2008);
- Reconstruction of a 3D model of a face from a 2D image (Song *et al.* 2012);
- Modelling of facial development in time (Morris *et al.* 1999);
- A unique characterisation of a face by means of a set of landmarks (Katina *et al.* 2011);
- Craniofacial superimposition (Yoshino *et al.* 1995);
- Diagnosis of genetic syndromes based on craniofacial dysmorphology (Hammond *et al.* 2004);
- Surgical planning, including reconstruction of partly missing or damaged face parts, e.g., automated analysis

Received 18 June 2012; accepted 29 October 2012

of 3D images of temporomandibular joint (Feltlová *et al.* 2010);
- Study of genetic disposition for the size and shape of facial features (Klimentidis, Shriver 2009).

Image analysis (image processing) is a highly developed discipline of computer science. Image analysis is not only devoted to the applications of information technology to images but is rather a self-standing scientific discipline with the aim of extracting information from images. Its numerous methods are capable of solving face detection and recognition tasks, which may bring inspiration for more complex computerised anthropological applications. Face localisation has the aim of localising the presence of a face in a given image, provided that the image contains exactly one face. Face detection has the aim of localising all faces in a given image. Face recognition is an identification task with the aim of assigning an image of a face to an individuals in a given database of individuals (Yang *et al.* 2002). Face recognition requires the performing of face detection as the initial step. The face has a characteristic structure and both humans and software procedures can reliably localise faces in a photograph. At the same time, the difference in face appearances of different individuals allows us to recognise each individual reliably from all other people. Therefore, in spite of the similarity among all faces, we can say that the variability among faces of different people is large enough to recognise each individual.

Image analysis methods can solve various tasks in anthropology objectively and precisely. They can simplify work that is carried out repetitively and quickly over large databases. Many recent software systems for anthropological applications identify themselves as computer-assisted or computer-aided. However, the majority use a computer only for data visualisation (Damas *et al.* 2011). A fully automatic procedure has not been implemented for example for craniofacial superimposition yet. For other tasks, such as facial reconstruction from a skull, there is a variety of methods available, which yield very different (and imprecise) results and there are no general recommendations in favour of one method over other ones (Wilkinson 2004).

Statistical methods play an essential role in modern anthropology (Lucy 2006). It is worth recalling that the first statistical methods were originally proposed for biological anthropology during the first half of the 20th century with the aim of extracting information from anthropological measurements. Actually, the foundations of multivariate statistics were laid by researchers analysing anthropological measurements (F. Galton, K. Pearson, R. A. Fisher, P. C. Mahalanobis, C. R. Rao). Current statistical methodology serves as a prominent tool for information extraction from anthropological images.

This paper presents a review of image analysis methods applicable to facial analysis tasks in anthropology. We study modern approaches based on up-to-date methods of statistics and computer science. Next section gives an overview of image analysis methods for various tasks of biological and forensic anthropology. It also describes principles of methods of face detection and face recognition, which have evolved in computer science. We also pay attention to promising methods of robust image analysis and apply them to dimension reduction and classification analysis in the context of mouth detection in real images.

IMAGE ANALYSIS METHODS IN ANTHROPOLOGY

Image analysis methods represent an inevitable but non-trivial tool for information extraction from 2D or 3D images in numerous anthropological applications. 2D images are acquired most commonly as grey-scale digital photographs with a value called grey intensity corresponding to each pixel. Grey intensities are commonly stored as absolute values in the form of integers in the interval [0, 255], or they are normalised to relative values in the form of rational numbers in the interval [0, 1], which again allow for 256 different intensities. Colour images are commonly represented in an RGB or HSV colour space. 3D images of faces or skulls can be acquired in the form of a 3D model using a 3D laser scanner, 3D stereo-photogrammetry, or computer tomography. Image analysis methods tailor-made for 3D anthropological applications are however only at the beginning of their development (Vanezis 2008) and there are only a few reliable systems available. We describe general principles of the most remarkable approaches to 2D and 3D image analysis of faces and discuss some representative examples.

Image analysis in general

Image analysis is a highly developed field of computer science, which offers numerous sophisticated methods for the complicated task of information extraction from images. The potential of various image analysis approaches is inspiring also for anthropological applications (Claude 2008). Besides, methods of image analysis give very reliable results also in a wide variety of such non-standard situations, which can be exploited in anthropology. Anthropological images are acquired under simplified (standardised) conditions and can often be captured repeatedly if their quality is not sufficient. On the other hand, we must say that software procedures available for image analysis may not be well adapted for the specific requirements of the anthropological context.

In general, we can say that image analysis (in a general context within computer science) is devoted to very complex tasks under specific settings, which allow to analyse also partially occluded faces (by glasses, pieces of cloth, hands, or background objects) or incomplete faces (with a part beyond the boundary of the image), faces captured in a different pose or with emotions, blurred faces in motion or faces photographed under bad conditions (fog, water drops on camera lens) (Felzenszwalb *et al.* 2010). Nevertheless, practitioners can confirm that even the best available commercial systems for face identification do not reach 100% reliability. Particularly identification systems based on the analysis of the whole face, which are claimed to be faultless have an amazingly low performance (Vančo 2005).

Reliable methods of image analysis are usually classified into one of two basic groups: model-based and appearance-based (Lu 2003). Model-based methods allow for model facial variability in an elastic (morphable) way, which makes them particularly suitable for facial images with remarkable facial expressions. Appearance-based (also view-based) methods do not deform the face and are usually based on a routine application of multivariate statistical methods, while intra-personal variability can be estimated from multiple images of each face. We will now describe common image analysis approaches for information extraction from 2D or 3D images.

Image pre-processing

Analysis of anthropological images always requires the correct pre-processing. Every 2D or 3D image requires an initial cleaning from noise, smoothing or filling of incomplete regions. Often the size and orientation of the face or skull in the image is a principal problem and manual standardisation is commonly performed. Facial analysis commonly considers only inner parts of faces and ignores hair and background around faces. If the pre-processing is not implemented properly, not even the best methods for image analysis can extract correct information from images.

Noise reduction (image denoising) aims to remove noise from (contaminated) images and recover the raw image (without contamination). Important aspects of noise reduction include edge preservation, retaining textures or singularities, and removal of deblurring. Noise reduction commonly assumes a probabilistic model with Gaussian noise with the same variability in each pixel (Kleihorst 1997). The noise reduction in 2D images is commonly performed by a two-dimensional filter, which is a transformation applied to the intensity values in a certain neighbourhood of each pixel. Pitas, Venetsanopoulos (1990) studied filters based on robust statistical methods. Hotz *et al.* (2012) considered noise reduction by means of a multi-resolution criterion, which tests a set of statistical hypotheses that the noise in all possible areas in the image is not significantly different from independent random variable with the Gaussian distribution.

Dimension reduction is often used also in anthropological applications as a preliminary step of image analysis, not only for very large images. It allows the simplification of consequent computations, to describe the differences among groups, to reveal the dimensionality of the separation among groups, and the contribution of variables to the separation (Quintiliano, Rosa 2006). An important general approach to dimension reduction is feature extraction, which replaces the raw image by a set of a smaller number of features in the form of a combination of original intensities from different pixels. The features may be defined, e.g., as edges or regions with a high contrast such as boundaries between different homogeneous areas in the image (Gonzalez, Woods 2008). However, any analysis of transformed data has a much more complicated interpretation than an analysis performed on the original data. Nevertheless, anthropologists often perform a dimension reduction by too simple and subjective (but rarely justified) methods (Baylac, Frieß 2005).

Principal component analysis (PCA) is the most common dimension reduction method. The method yields reliable results only after a prior standardisation of faces (Hancock 2000). Frowd *et al.* (2005) used the principal component analysis in a facial reconstruction system helpful for crime witnesses. Quintiliano, Rosa (2006) considered principal component of mouths (called eigenmouths) and eyes (called eigeneyes) as elements of a face recognition procedure. PCA applied to the whole faces considers a particular face as a distortion from the average face and principal components (called eigenfaces) are used as effects which contribute to the most typical (and most variable) differences from faces from the average (Hancock 2000). They can be further deformed by eigenshapes which are obtained as principal components of shapes. Additionally, artificial faces can be randomly generated from the average face by including a random effect of eigenfaces, possibly after a random morphing according to eigenshapes. Nevertheless, the principal component analysis has been criticised as unreliable for high dimensional data (Dai *et al.* 2006).

Fisherfaces represent a dimension reduction method alternative to eigenfaces, which performs more reliable for facial images with a larger variations in illumination and facial expression. It was proposed by Belhumeur *et al.* (1997) for the task of face recognition. It can be derived from the linear discriminant analysis (LDA), which is a classification method with the ability to be used also as a dimension reduction method. In contrary to PCA, the LDA allows to reduce the dimension of given images in a class-specific way, i.e., the class membership of each image is used to retain a separability between groups. The LDA is however computationally infeasible for real images, if their number in a given database is smaller than the number of pixels in each image. Therefore, the method of Fisherfaces starts by performing the PCA on the set of all images. Each image is replaced by a set of several principal components. Finally, the LDA is performed on this set to assess a further reduction of the dimensionality of the data.

Template matching

Template matching is a tailor-made method for face detection in raw images, which has found applications also in the analysis of anthropological images. A template can be defined as a typical form, an ideal object or model. Template matching has various applications to detection of objects in given images. References on face detection and recognition describe templates for the whole face, for parts of the face (mouth, nose, each eye) or for face silhouettes (Yang *et al.* 2002). We can distinguish between rigid (non-deformable) and deformable templates in the task of face detection.

Rigid template matching is performed in the following way. A particular template is placed on every possible position in the image and the similarity (correlation) is calculated between the template and each part of the image, namely the grey intensity of each pixel of the template is compared with the grey value of the corresponding pixel of the image. The area of the image with the largest similarity with the template is classified to correspond to a mouth. Alternatively, it is possible to use the following approach. The area which has a similarity with a particular template exceeding a given threshold is classified to be a mouth (Wei *et al.* 2011). If several templates are used, the largest similarity over all templates is considered. Template matching can be interpreted as a statistical problem of calculating the similarity between the template and the image. In most applications, the Pearson correlation coefficient is used to calculate this similarity.

To the best of our knowledge, a sophisticated construction of rigid templates has not been investigated yet. Let us consider the task to automatically localise a mouth in facial images. Computer scientists recommend to construct templates as mean of real mouths of several different individuals. However, such approach is not optimal. It is true that a template should be very similar to real mouths but at the same time very different from all possible non-mouths (parts of the image not corresponding to a mouth). From the anthropological point of view, there seems to be no clear recommendation about a suitable appearance of a mouth template.

Although the idea of rigid templates is relatively simple, they are powerful and have a clear interpretation. Templates are also the basis for other methods. These include methods for face localisation based on a combined search for particular facial features, which exploits individual templates for a mouth, each eye, nose *etc.* Other examples include templates applied after computing a wavelet transformation of images or methods of geometric morphometrics, which will be described in section *Geometric morphometrics*. Now we will discuss examples of approaches which are based on rigid templates.

Vanezis *et al.* (2003) quantified differences between facial features of Negroid and Caucasian male faces. A facial reconstruction procedure was proposed to deform the face optimally to correspond to the skull. A 3D facial image from a black male was used as a rigid template over a Caucasian skull. Further, the shape of the nose and lips were transformed to correspond to Caucasoid average measurements. The research was used to study the role of facial appearance in the development of racial stereotypes.

Dobeš *et al.* (2004) proposed a rigid template matching method for person recognition based on iris images. The set of templates contains three images of the left iris and three images of the right iris of each of 64 individuals. If a new individual should be recognised, the image of his/her iris is compared with all templates. The similarity between the new image and each particular template is calculated by mutual information, which is a similarity measure common in information theory (Cover, Thomas 2006). When this exceeds a given threshold, the iris is classified to belong to the same individual as the template.

Wei *et al.* (2011) analyzed fragmented skulls for both archeological and forensic applications exploiting rigid 3D skull templates, which are obtained as 3D skull models of different individuals. The method aligns each fragment with a skull template. The Pearson correlation coefficient is used to measure correspondence between all points of a skull fragment and all corresponding points of the template. Then the method allows to restore missing regions in the fragmented skull, exploiting the symmetry of the skull.

Deformable template matching

Deformable 2D templates represent a more flexible alternative of rigid templates, allowing shape alterations. Deformable templates allow to combine ideal shape of facial features together with individual variability, which explains their popularity in face detection tasks in image analysis.

The most common approach to deformable template matching in facial image analysis is to consider deformations of a rigid template. Let us consider the task of mouth localisation in the image of a face. Stretching, shift, and rotation of the whole mouth template or its part are possible forms of deformations, which are used to make the template as similar to each part of the image as possible. The deformations can be described by tuning parameters of simple (smooth) functions. Such an area of the image is classified as corresponding to the mouth, which requires the smallest deformation of the mouth template over all areas of the image. The computation of the optimal deformation makes the computation much more demanding compared to rigid template matching. Deformable templates have the advantage of being suitable for noisy images or occluded objects. A mathematical theory of deformations and deformable templates was developed by Grenander (1993) and Downie, Silverman (2001).

We will now describe popular methods commonly applied in the image analysis of faces. Some of them are based on the concept of landmarks (landmark points), which have to be placed on each face by an experienced anthropologist. Landmarks serve as points of correspondence (exactly defined biologically or geometrically) among different faces and also among different images of the same face (Bookstein 1991, Dryden, Mardia 1999). Anthropometric measures such as distances and angles between such intuitively selected landmarks and areas surrounded by them are investigated. Examples of landmarks on a face include the soft tissue points as left/right *endo*- and *exocanthion*, left/right *cheilion* or *labiale superius*, and *labiale inferius* (see, e.g., Farkas 1994 for details). Selection of landmarks is a strenuous and complex procedure requiring considerable anatomical understanding (Weber, Bookstein 2011). Bookstein (1991) formulated a classification of 2D landmarks to three categories:

1. Juxtaposition of tissues;
2. Maximum curvature points;
3. Extreme points (also described as "the most anterior points" or "the farthest points" from a landmark) and constructed landmarks (perpendicular projections, radial intercepts *etc.*, see Bookstein 1991: 65). A caution on their utilizing was given, e.g., by Ross *et al.* (2010).

Deformable template matching can be performed by means of active shape models (Cootes *et al.* 1995). A set of landmarks is manually localised in a training set of images, which have to be aligned by scaling, rotating, and translating, e.g., by Procrustes analysis. The average shape over the training data set is computed and also the variability of the shape corresponding to each of the landmarks. The principal component analysis allows us to obtain eigenshapes as the most important shape deviations from the average shape. The original template is deformed by means of various combinations of the average shape with the principal shapes. A probabilistic model is able to quantify the deformation of each given shape from the average shape. The deformable template matching searches for an object, which has the least deformation from the template.

Active appearance models (Cootes *et al.* 1998) represent an improvement of active shape models. They calculate the shape variation as well as the appearance variation. In greyscale images, the method quantifies the variability in grey intensities in each pixel. A probabilistic model quantifies the deviation of a given object from the template, using also the knowledge about the variability of the grey intensities in individual pixels.

A less frequent approach is to consider deformable templates in the form of a collection of curves. Such templates are placed on every position in the image and parameters of the curves yielding the best match with the image are found. Yuille *et al.* (1992) applied such deformable eye template within a procedure for face recognition. An eye template is constructed as a circular centre bounded by two pieces of parabolas. Adjusting the parameters corresponds to rotating the template and adjusting its size and shape. The method deforms the template to match the image and such part of the image is classified to correspond to the eye, which requires the smallest (simplest) deformation. Similarly, two parabolas serve as a deformable template for a mouth, while one parabola corresponds to a contour of the upper lip and the other parabola to a contour of the bottom lip.

Another possibility is a combination of deformable templates with active contour models (snakes) studied by Horbelt, Dugelay (1995). Snakes represent a method for detecting edges, lines, and contours by searching for boundaries between areas of high and low intensity (Kass *et al.* 1988). The combination of deformable template matching with snakes improves the stability of the approach.

Classification analysis

The most important multivariate statistical tasks for the task of extracting information from anthropological images is classification analysis, which is designed to quantify the differences among groups and to construct a decision rule (classification rule) for group identification. It allows, e.g., to classify a new face to one of several groups (Farkas 1994). The most common classification method in the analysis of anthropological images is LDA, which is based on Mahalanobis distance of a new observation from the mean of each given group. It was proposed by Fisher (1936) for an application in craniometry.

Anthropological tasks can exploit the ability of classification analysis to distinguish between the interpersonal and intra-personal variability, which is at the same time helpful in face recognition in computer science. Identification methods are typically learned over a training database of samples; to assess the performance of an identification rule, validation studies are usually performed on independent validation samples. An example of a classification problem is the task to construct a classification rule that automatically classifies a new skeleton either to be male or female based only on anthropometric measurements (Smith 1999).

A modern approach to classification analysis is based on machine learning methods, which include artificial neural networks or support vector machines (Er *et al.* 2005). They are very flexible but contain a large number of parameters and therefore their tuning requires a very large number of samples, which may be unavailable in practical problems. They can be described as black boxes, which do not allow a clear interpretation of the parameters to be found. Machine learning methods are trained to learn characteristic properties of all faces and also non-faces (all other parts of the image not corresponding to a face). However, the set of all possible non-faces is huge and the methods fail to find optimal values of the parameters. More complicated classification methods have a tendency to suffer from overfitting, which means that they exploit too specific properties of the observed samples and consequently perform only weakly in classification of new independent samples (Buk *et al.* 2012). Therefore, a simple classification rule may be more desirable in practice. Sometimes, classification methods are constructed as combinations of several very simple individual classification methods.

Let us discuss the connection between template matching and the LDA. We explain this on the task of mouth localisation. Let us consider a task to decide if a certain image Z, which is a part of an image I containing a whole face, corresponds to a mouth or to a non-mouth. The LDA calculates the distance of Z from the average mouth and the average non-mouth. Then, Z is classified to that group, which has its average closer to Z. We can say that the average mouth represents the prototype of all mouths and the average non-mouth the prototype of all non-mouths, although the average non-mouth has no anthropological interpretation and is rather arbitrary in real applications. On the other hand, the template matching can be characterised as a simplified version of the LDA, because it assumes the intensities in all pixels to be uncorrelated and assumes the variability of the intensities to be the same across pixels. The mouth template is a prototype of all mouths, while a prototype of all non-mouths is not considered. Template matching considers all areas in I and assigns Z to be a mouth, if and only if Z has a smaller distance from the template among all areas in I.

Most common multivariate statistical methods suffer from a so-called curse of dimensionality (van de Geer, van Houwelingen 2004). They are unsuitable for the analysis of data with more variables (e.g., pixels) than analysed samples (e.g., individual images) and lead to a collapse of the LDA or other methods. They are also unsuitable for analysing images, particularly in smaller databases. On the other hand, classification analysis is known to perform weakly if preceded by common dimension reduction methods; in such a case, it has been recommended to use dimension reduction methods tailor-made for the classification purposes (Dai *et al.* 2006). Special classification methods for highly dimensional data and their fast computational algorithms have been studied, which have usually the form of a modified LDA (e.g., Guo *et al.* 2005).

Geometric morphometrics

Morphometrics is a discipline devoted to a study, visualisation, and quantification of 2D or 3D shapes. It describes a shape by a set of numbers and is devoted to shape variability and quantitative comparisons of shape with other variables (Claude 2008). The shape is defined as such geometric information, which remains after filtering location, scale, and rotational effects out from an object. This makes the methodology suitable exactly for the analysis of such features in the face, which differ in terms of shape, size, or colour. Morphometrics can be described as a boundary field between morphology and multivariate statistics (Zelditch *et al.* 2004). We can distinguish between traditional morphometrics and geometric morphometrics, while the latter includes methods based on landmarks or outlines (outline analysis).

Traditional morphometrics describes shapes mainly by means of distances between landmarks and angles of line segments. This is not sufficient to describe the shape of a face completely. Therefore, the reliability of traditional morphometric methods has been criticised (Katina *et al.* 2011, Zelditch *et al.* 2004).

The landmark-based geometric morphometrics is the most common and most successful approach in modern geometric morphometrics. In addition to landmarks, semi-landmarks are considered, which are defined as "points without anatomical identifiers but satisfactory for subsequent morphometric interpretation" (Bookstein 1991). Semi-landmarks can be characterised as "points along a curve" with an arbitrary position at the curve (Zelditch *et al.* 2008), which "carry less information than landmarks". The statistical analysis of data in geometric morphometrics is more complicated compared to traditional morphometrics, which is a consequence of the correlation structure among the coordinates of individual landmarks. Katina *et al.* (2011) described various sources of measurement errors in traditional and geometric morphometrics together with possibilities of their minimisation and classified landmarks and semi-landmarks by comparing the reliability of their identification.

The localisation of landmarks in a particular face is most commonly performed manually in various tasks of morphometrics. Currently, the accuracy of any available system is still "worse than manual identification in every study" (Leonardi *et al.* 2009). This crucial step is strongly influenced by the biological question guiding the analysis (Knussman 1988). Examples of an automated procedure for the identification of landmarks include the work of Hutton *et al.* (2000), who used active shape models (cf. section *Deformable template matching*). In this context, e.g., a deformable mouth template with manually identified landmarks is deformed to obtain the best fit with a new image and the landmarks in the mouth are identified as points corresponding to the landmarks of the deformed template at the position of the best fit. Palaniswamy *et al.* (2009) used rigid template matching after a feature extraction.

The main landmark-based method for shape registration (alignment) used in geometric morphometrics is Procrustes analysis. Shape registration methods perform a shape matching between two shapes annotated by landmark configurations. Particularly, they are commonly used to deform a set of facial landmarks in one face into precise alignment with landmarks of another face. As a consequence, they are able to standardise a face to correspond to the average landmark configuration.

The thin-plate splines can be described as an algorithm for a computation and visualisation of a deformation, which transforms one image to another (Bookstein 1989). Each of both images needs to have an identified set of landmarks. The method constructs a function transforming landmarks from one image to correspond exactly to the landmarks of the other image, while the remaining points are transformed by a function as smooth as possible. A thin-plate spline model is computed by minimizing bending energy between the two images. If 2D images are considered, the deformation of the image is analogous to placing the image on a thin sheet of metal and bending the metal by a 3D deformation.

Partial Procrustes Analysis (PPA) is used for a shape registration of two objects, while the term Generalised Procrustes Analysis (GPA) is used for a set of three or more shapes. The shape analysis is converted to a standard multivariate statistical analysis by means of a transformation (Procrustes tangent projection), which replaces coordinates of the landmarks by so-called Procrustes tangent coordinates

(Kent, Mardia 2001). The consequent shape registration is performed by an optimisation in both the PPA and GPA based on a least squares criterion, aimed at minimizing the distance between the sets of landmarks. The distance is called partial Procrustes distance in the context of the PPA and full Procrustes distance in the GPA. Nevertheless, the methods of landmark localisation may result in missing points on some shapes, landmark outliers, and even errors in the correspondence between landmarks (Larsen 2008). Therefore, alternative approaches have been proposed for the PPA (Dryden, Walker 1999) and GPA (Crosilla, Beinat 2006), which are highly resistant to outlier points.

Landmark-based methods of geometric morphomemtrics are helpful in the task of 3D facial reconstruction, which has the aim of constructing a 3D model of a face from a given skull. The process exploits one or several templates. Each of particular templates is selected as a 2D image of a face of another (arbitrary) individual and a set of anatomical landmarks is located in this image. The template face is commonly selected to have a corresponding age, sex, origin, and body construction, which are recognised from the whole skeleton of the corpse. The set of landmarks in this facial image serves as a rigid template, which is compared, to a set of craniometric landmarks, located in the 3D image of the skull. The procedure is usually repeated with several templates and finally the template with the best similarity with the skull is selected. Existing procedures still strongly depend on the choice of the arbitrary facial templates (Vanezis 2008).

Landmark-based methods of geometric morphometrics are also used in the task of craniofacial superimposition, which is a time consuming process with the aim of deciding if a skull of a crime victim corresponds to a particular face, which is captured in a 2D image. Methods of geometric morphometrics are based on a manual location of craniometric landmarks in a 3D image of the skull and also manual location of anatomical landmarks in a 2D portrait image of the face (Damas *et al.* 2011). The image of the face plays the role of a deformable template, which is deformed to match the skull. The landmarks are located in those parts of the face where the thickness of soft tissue is low and can be estimated reliably. Here a skull-face overlay guided by landmarks is an important part of the whole process. Instead of comparing distances between pairs of landmarks, proportions among landmarks are considered. There has been no method proposed for an automatic localisation of landmarks on a skull. In the future, such methods could be inspired from the face recognition, which is a task with many reliable automatic methods for landmark localisation. The similarity between a face and a skull is calculated. An overview of landmark-based methods of geometric morphometrics for comparing a skull of a crime victim with 2D facial images of missing individuals was given by Damas *et al.* (2011).

Böhringer *et al.* (2006) used landmark-based geometric morphometrics for a diagnosis of genetic diseases based on craniofacial dysmorphology. The procedure is started with a careful manual identification of 40 landmarks in each image of the face by an anthropologist. The first aim is the automatic localisation of a face in a new image. A 2D wavelet transformation is performed, which replaces the raw image by a set of images with different resolutions, which are always smaller than resolution of the raw image. The face localisation is performed by rigid template matching in the set of images. Here it is hoped that noise is suppressed in images with a smaller resolution, while the facial components remain. The next step is the classification of the face to one of ten syndromes, which is based on distances between two individual landmarks on the face. The decision support performs remarkably well with a correct performance in more than 90% for all syndromes, which exceeds the performance of an experienced geneticist.

Other recent results on landmark-based geometric morphometrics include, e.g., the work by Eliášová, Krsek (2007), who proposed a mathematical description of 3D distortions of skulls for craniofacial superimposition. Bigoni *et al.* (2010) used landmark-based geometric morphometrics to learn a classification rule for determining sex from the shape of a skull.

Outline analysis (outline morphometrics) is a morphometric methodology based on a quantification of outlines, which have to be traced manually or with software. Standard classification analysis can be applied on the outlines instead of analyzing the raw data. Previous applications used the principal component analysis or Fourier analysis for dimension reduction. However, different methods give different results and there is no underlying theory allowing the selection of the best method (Adams *et al.* 2004).

Robust image analysis

We understand robust image analysis to represent a branch of image analysis, which is based on methods of robust statistics. However, the concept of robustness has rather a general meaning in image analysis. It is usually connected with reliability of methods under non-standard situations such as different illumination, rotation or size of objects in the images (Yang *et al.* 2002).

Robust statistics represents a modern approach to statistical analysis of data, which was originated already in 1960s (Stigler 2010), but has obtained a larger attention only in recent applications. Their motivation is the high vulnerability of numerous classical statistical methods to noise or outlying measurements (Heritier *et al.* 2009). The high vulnerability to noise obstructs statistical methods commonly applied in anthropology, e.g., the Pearson correlation coefficient, LDA, PPA, or GPA, Bayesian statistical methods, machine learning procedures, various dimension reduction techniques. Another common problem is a high sensitivity of classical statistical methods to special assumptions, which are often violated in anthropological applications, such as normal distribution of the measurements or equality of variances across measurements.

Robust statistical methods are not sensitive to the presence of noise or outlying measurements in the data (Jurečková, Picek 2006). Breakdown point has become a crucial concept of robust statistics. It is a statistical measure of sensitivity of a statistical method against noise or outliers in the data, which measures the minimal fraction of data that cause a collapse of a method when set to arbitrary values. In the analysis of images, the breakdown point of a given method corresponds to the minimal fraction of pixels which can be contaminated by arbitrarily heavy noise with the effect of a collapse of the method.

Robust versions of many classical statistical methods have been proposed, which include a robust correlation coefficient, LDA, principal component analysis or robust estimation procedures for linear regression model (Shevlyakov, Vilchevski 2002). Methods of robust statistics have often the form of modifications of classical statistical methods; completely new principles are used only rarely.

Methods of robust image analysis applied to facial images turn out to be resistant to various sources of noise in the image or occlusion of the face, asymmetry in the face or in the background or to modifications of hair style (Kalina 2012a). The methods do not rely on the assumption of normal distribution of the grey intensities. Robust template matching was studied by Chen *et al.* (2003), who used a robust measure of similarity between the template and the image. Robust methods may be desirable also for the 3D analysis of images of skulls, because they can be insensitive to a bad condition of a skull (scratches, dirty or burned surface or missing fragments). Robust methods can be expected to be insensitive to the preliminary cleaning of the skull. If robust image analysis methods are used, it is not so important to pay attention to a prior noise removal from the images. So far, methods of robust image analysis have not been sufficiently exploited in anthropology. Therefore, we will present their illustration in an image analysis application in the next section.

Application of robust image analysis to mouth detection

We present a study on mouth detection, which brings arguments in favour of robust approaches to the dimension reduction and classification analysis. Throughout the section, we will use the term non-mouth for any such area in the images, which does not contain the mouth. In our previous work, we used rigid template matching to localise the mouth or eyes in the images in our previous study (Kalina 2010), where we verified templates to be a reliable method for face recognition. In the present work, we compare the performance of various robust methods for dimension reduction and classification analysis with results obtained with standard (non-robust) methods.

We work with a database of 212 grey-scale 2D facial images from the Institute of Human Genetics, University of Duisburg-Essen, Germany (projects BO 1955/2-1 and WU 314/2-1 of the German Research Council) taken for medical purposes in human genetics (Böhringer *et al.* 2006). Each of the images contains exactly one face in the age between 18 and 35 years. The database contains 92 images of males (43%) and 120 females (57%). No two images correspond to the same individual. The faces are considered to be a representative sample from individuals with German origin. Each of the images in the database is a matrix of the same size 192×256 pixels. Images were taken under the same conditions, which were intended to be as much standardised as possible. Each photographed individual was looking straight at the camera. The faces have about the same size and contain no facial expressions. However, some faces are rotated in the plane by small angles. We implemented all computations in R software package (R Development Core Team 2012).

We inspect the ability of robust classification analysis in the task of mouth detection. From the database described above, we manually selected each mouth and also the non-mouth that has the largest similarity to a mouth template as measured by the Pearson correlation coefficient. Each of the mouths and non-mouths has the size 26×56 pixels. The training database consists of 124 images of the mouth and 124 images of the non-mouth from the same images, which were selected at random from the original database. The validation database contains 88 mouths and 88 non-mouths from the remaining images. The aim is to learn a classification rule which would be able to classify a new image of the size 26×56 pixels as a mouth or a non-mouth.

We compare several approaches. However, the number of pixels in each image exceeds the number of images. The LDA is computationally feasible also in this high-dimensional context exploiting, e.g., the Moore-Penrose

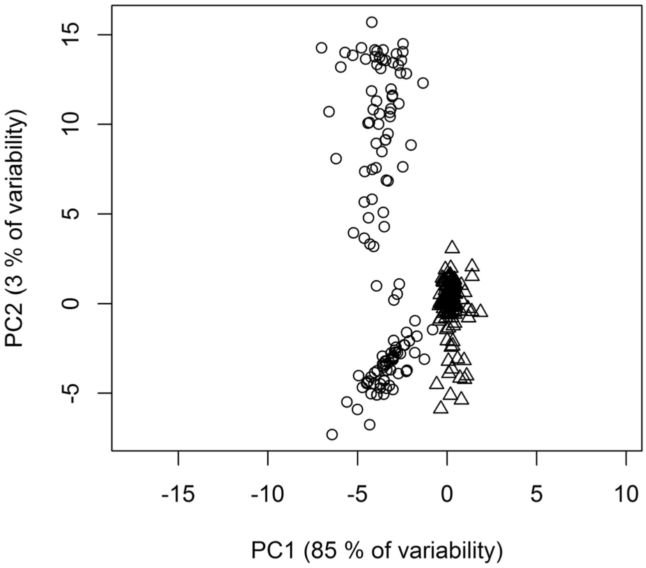

FIGURE 1. Plot of two robust principal components computed from a set of 124 mouths and 124 non-mouths using the projection pursuit method. Values corresponding to mouths are denoted by a bullet and values corresponding to non-mouths by triangles. Based on this transformation of images to only two-dimensional values, the LDA has the ability to separate the two groups with a performance correct in 100% of cases.

pseudo-inverse, but its classification performance is not good enough (Tebbens, Schlesinger 2007).

Firstly we use a dimension reduction by one of the following methods: PCA, projection pursuit PCA (PP-PCA) proposed by Croux *et al.* (2007), and robust principal component analysis based on implicit weighting (Kalina 2012a) denoted as LWS-PCA, where LWS is an abbreviation of the least weighted squares estimator of Víšek (2002). For each of the methods, we keep five main principal components computed from each image. The projection pursuit algorithm can be described as a general robust method for finding the most informative directions or components for multivariate data, searching for such principal components of the data that explain the largest portion of variability. The plot of two robust principal components computed from the data by the PP-PCA is shown in *Figure 1*. It shows the first robust principal component to be able to separate mouths from non-mouths well.

The rule of the classification analysis is applied only to five principal components representing each image. We use either the LDA or its robust counterpart denoted as MWCD-LDA proposed by Kalina (2012b), where MWCD is an abbreviation of the minimum weighted covariance determinant estimator. The classification rule of the MWCD-LDA is obtained as a robust analogy of the LDA obtained by replacing the mean and co-variance matrix estimators by their robust counterparts. The classification performance of different methods is compared in *Table 1*.

TABLE 1. Mouth detection: comparison of different methods for dimension reduction and classification analysis. Classification performance computed over a set of 124 mouths and 124 non-mouths (relative frequency of correct results).

Dimension reduction	**Classification method**	**Classification performance**
PCA	LDA	0.95
PP-PCA	LDA	1.00
PP-PCA	MWCD-LDA	1.00
LWS-PCA	LDA	0.95
LWS-PCA	MWCD-LDA	0.98

PCA, principal component analysis; PP, projection pursuit; LWS, least weighted squares; LDA, linear discriminant analysis; MWCD, minimum weighted covariance determinant estimator.

The best results are obtained with the PP-PCA method allowing robust dimension reduction. In general, the robust approach may bring benefits to various identification tasks in anthropological applications. A disadvantage of the robust approach may be a high computational complexity. Furthermore, there is a popular misbelief that robust methods do not require any statistical assumptions. However, they only relax an assumption concerning the distribution of the data, while other standard assumptions need to be fulfilled as well (Jurečková, Picek 2006). Moreover, outliers in images should be examined more carefully before they are thoughtlessly ignored or down-weighted.

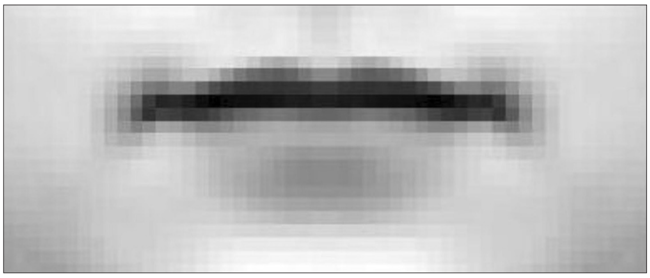

FIGURE 2. A mouth template obtained as the mean of 10 mouths of different individuals.

The next study presents an illustration of principles of robust template matching. We constructed a mouth template (*Figure 2*) as the average of 10 mouths of the same size 21×50 pixels, which correspond to different individuals. *Figure 3* shows a particular mouth and *Figure 4* a particular non-mouth. Template matching using the Pearson correlation coefficient comes to the conclusion that the similarity between *Figure 2* and *Figure 3* is larger than the similarity between *Figure 2* and *Figure 4* (see *Table 2*), while the robust LWS correlation coefficient (Kalina 2012a) is able to separate the mouth from the non-mouth in a much stronger way, which is a quite typical situation.

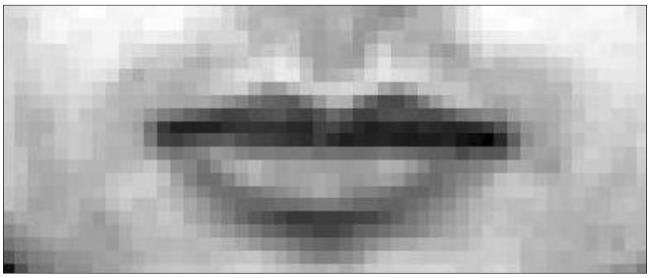

FIGURE 3. A mouth.

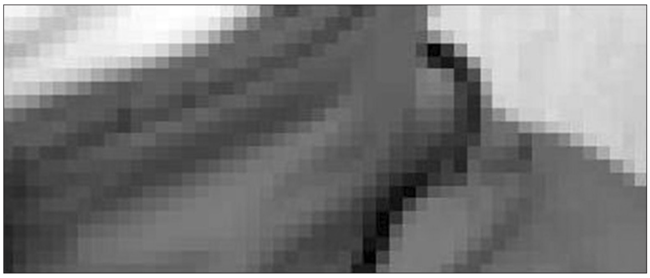

FIGURE 4. A non-mouth.

TABLE 2. Values of similarity between a mouth template (*Figure 2*) and a mouth (*Figure 3*) and between the same template (*Figure 2*) and a non-mouth (*Figure 4*).

	Template & mouth	**Template & non-mouth**
Pearson correlation coefficient (classical)	0.38	0.31
LWS-correlation coefficient (robust)	0.44	0.10

LWS, least weighted squares.

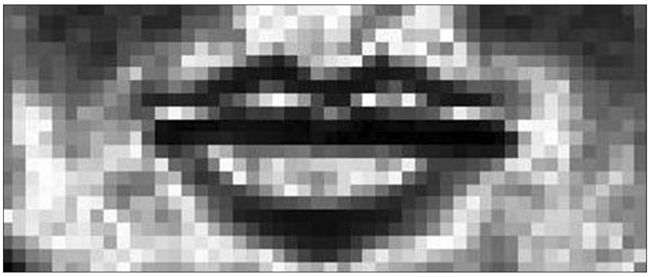

FIGURE 5. Weights determined by least weighted squares method for the mouth of *Figure 3* using the template of *Figure 2*.

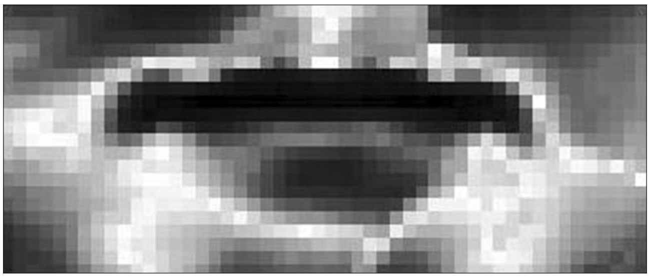

FIGURE 6. Weights determined by least weighted squares method for the non-mouth of *Figure 4* using the template of *Figure 2*.

Further, we discuss the results of *Table 2* obtained by the LWS correlation coefficient, which assigns weights to individual pixels of the images. *Figure 5* shows the weights for the similarity between *Figure 2* and *Figure 3*.

The LWS correlation coefficient can be interpreted as a weighted version of the Pearson correlation coefficient with these weights. Black pixels are now pixels with small weights, which may interpreted as outlying grey intensities in the comparison of *Figure 3* against *Figure 2*. White pixels correspond to areas with a large similarity between the two images. We can see that some areas of the lips represent a structure common to both the template and the mouth. In an analogous way, *Figure 6* shows the weights for computing the robust similarity between *Figure 2* and *Figure 4*. The method recognizes that the lips are recognised as the main structure not present in the non-mouth of *Figure 4*, which explains the very low value of the robust correlation coefficient between *Figure 2* and *Figure 4*.

CONCLUSIONS AND OUTLOOK

This paper gives an overview of image analysis methods applicable to facial anthropology. Current anthropological methods do not fully exploit the potential offered by image analysis methods. We can say that face is the most commonly studied object of pattern recognition, because a face represents a very reliable identification tool (Rak *et al.* 2008). The face as object of interdisciplinary research is already commonly applied in security systems, identity cards, at airports (cameras in the halls or pass controls with people standing without movement) or other public areas.

However, fully automated, computerised methods are not available for a variety of anthropological applications concerning the face. This paper gives an overview of some methods for analysis of facial images, which are either directly applied to the context of biological and forensic anthropology. Other methods developed within computer science for the tasks of face detection and face recognition may bring inspiration for a possible usage in both biological and forensic anthropology.

In anthropological practice, it is certainly important to know how to select a suitable method for a particular task, because the equipment for capturing anthropological images is expensive and the user wants to be sure that the data collected by expensive technology are analysed in a proper way. However, we cannot give many general recommendations on the selection of methods, because it strongly depends on the particular context and available technology (Damas 2011). Systematic comparisons of different image analysis approaches to anthropological tasks have never been performed, mainly because of a wide diversity of different tasks or small sizes of samples in particular studies. In forensic applications, a systematic evaluation of different methods is complicated also by the fact that there are no publicly available databases of forensic anthropology data.

We presented a method for mouth detection based on robust statistics. We showed that robust methods bring benefits to dimension reduction and classification analysis in the context of face detection. Robust image analysis methods have the potential to be applied in anthropological applications, in which the presence of noise in images is an important issue. The methods are insensitive to noise in the images and at the same time have a potential to solve various anthropological tasks with the advantage of a clear interpretation. Possible areas of future applications include robust measures of similarity between a 3D model of a skull and a 2D image of the face in craniofacial superimposition.

Both biological and forensic anthropology contain many open problems which can be solved by means of image analysis. The main area of future research can be expected for the 3D analysis of anthropological images of faces or skulls, which may be inspired by available 2D approaches. However, it is necessary to say that 3D images are significantly more complicated structures than 2D images. There have been proposed no fully automated methods for craniofacial superimposition. Furthermore, current methods of 3D analysis are known to be too sensitive to the position of the skull in the 3D image. Other tasks for a future research include a systematic comparison of methods of image analysis in anthropological tasks or a modification of methods of robust image analysis to match specific needs of anthropological applications.

A promising future tool for an automated analysis of some anthropological images can be described as decision support systems, which are automated software systems which compare different possibilities in terms of their risk. The final decision in anthropological decision support systems should always belong to the anthropologist, who makes decisions based on data and knowledge and also carries the responsibility for the decision. Their usage requires training in the foundations of information sciences and analytical thinking as well as theoretical principles of statistical data analysis and decision making. Although decision support systems have already spread in some areas of medicine (Kalina, Zvárová 2012), they have not been introduced for anthropological applications yet.

ACKNOWLEDGEMENTS

This work is supported by RVO: 67985807. The author is grateful to two anonymous referees for valuable comments and suggestions for improving the paper.

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