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4D Analysis of Facial Ageing Using Dynamic Features

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Abstract

Facial ageing analysis based on 4D data (3D plus time) is much more robust to pose changes and illumination variations than using 2D image and video. The purpose of this investigation was to measure the effects of age and gender related facial changes using dynamic 3D facial scans. Experiments were carried out on the subjects, who were divided into two groups by age (15-30 years and 31-60 years). Each group was further subdivided by gender. 3D scans of the subjects were processed to extract facial features which were tracked through the duration of the data capture. Subsequently, a set of dynamic features were computed from these facial features, as well as static features for comparison. Two-way multivariate analysis of variance (MANOVA) of these features demonstrated that statistically significant age and gender related differences could be detected. We show that 3D facial dynamics provide more useful information than static features for the characterisation of smiles.

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Keywords: Smile; Dynamic Features; Age Grouping; Gender

1. Introduction

The human face conveys important information related to personal characteristics, including identity, gender, ethnicity and age. Age can play an important role in many applications such as age estimation in crime investigation, age-adaptive targeted marketing, age-invariant person identification[1] and is also the main risk factor for many complex diseases[2]. As facial ageing is one of the most prominent and accessible phenotypes of human ageing, it is important for assessing the risks of age-related diseases and for designing individualised treatments[3]. Ageing is an inevitable process that leads to many soft tissues changes, and this process particularly affects the lips, causing many changes such as thinning, and an increase in length[4,5]. Since the ageing process can change the characteristics of the smile, it is critical to acquire knowledge of age-related facial changes to inform the above applications. Automatic classification of faces into different categories based on gender, identity, age, ethnicity, facial expression and other

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face characteristics, is an essential element of facial analysis. Although there has been a great deal of progress in face analysis in the last few years, many problems remain unsolved. The design of algorithms that are effective in discriminating between males and females, or classifying faces into different age categories is still a major area of research[6]. Moreover, research on analysis of facial dynamics encounters many challenging problems, especially in the context of ageing.

However, gender differences in age-related change in the 3D dynamics of smile have been, to date, unexplored. A lack of suitable datasets in particular proving to be the limiting factor. To address this issue we have performed a study using 3D videos of closed mouth smiles for 80 subjects to determine whether ageing affects smile expressions. We have investigated and shown that the lips becoming less elastic and mobile with increased age is a factor, and we investigated whether gender played a role in the smile dynamics.

2. Related Work

In recent years, researchers have attempted to quantify facial ageing effects through various strategies. Ageing has been considered as the fourth dimension[7,8]. The human face undergoes many skeletal and soft tissue cellular changes, due to age progression which consequently affects its functional behaviour [9,10]. Studies have shown that lips become less elastic and less mobile with ageing[11,12]. Oral structures such as teeth and periodontium also change with age. Due to these changes the smile can be affected. Moreover, facial movements differ between the genders, especially in adulthood[13]. Recent psychological studies show that men and women have different smile behaviour[14]. However, in many studies on smile aesthetics, these results were not statistically tested[15,16]. Geld[15] and Desai et al[16] recently studied age related changes in smiles using videos. In this work, gender differences in age related changes in smiles were not explicitly identified. Due to the lack of information concerning gender and age differences, Chetan et al.[17] proposed a cross-sectional study to determine the trends and patterns between the different ages groups, and to determine if gender plays an important role. The findings from this study were:

- There is a difference between male and female smiles, and smiles also change with age.
- As individuals age, there is a loss of muscle tone which leads to a reduction in the height of smiles.
- During a smile, females exhibit greater horizontal movement and males exhibit greater vertical movement.

Facial dynamics yields further information allowing for more detailed analysis. This allows for greater discrimination across larger age differences. In the last decade, dynamic features of smiles (such as duration, speed, and amplitude of smiles) have received attention as opposed to morphometric cues to discriminate smiles. Cohn et al.[18] analysed correlations between lip-corner displacements, head rotations, and eye motion during spontaneous smiles. In another study, Cohn and Schmidt[19] reported that spontaneous smiles have a smaller onset amplitude of lip corner movement, but a more stable relation between amplitude and duration. Furthermore, the maximum speed of the smile onset is higher in posed samples, and posed eyebrow raises have higher maximum speed and larger amplitude, but have shorter duration than spontaneous ones. Linear discriminant classifier were proposed to distinguish between spontaneous and deliberate enjoyment smiles using duration, amplitude, and duration amplitude measures of smile onsets. They analysed the significance of the proposed features and showed that the amplitude of the lip corner movement is a strong linear function of duration in spontaneous smiles, but not in deliberate ones.

Krumhuber et al.[20,21] studied the effects of dynamic attributes of smiles in human and synthetic faces, and whether facial dynamics tell us something about the genuineness of an emotion. The findings demonstrate that the participants who showed an authentic smile were perceived as more likeable, attractive and trustworthy than those who showed a fake smile or a neutral expression.

Recently, Dibekliolu et al.[22] proposed a method to use facial expression dynamics, and produced a database to explore the effect of dynamic features for age estimation. In another study the dynamic features are used for age estimation using a person's smile and it was shown that the facial expression dynamics with appearance information are much more reliable for group classification tasks. Furthermore, experiments were carried out on disgust expression to evaluate the effectiveness of the proposed method in this study on a different expression and the results significantly improve the age estimation accuracy[23]. In addition, Dibekliolu et al.[24,25] proposed using the dynamics of eyelid, cheek, and lip corner movements to distinguish between spontaneous and posed smiles, where distance-based and angular features are defined in terms of changes in eye aperture.

Fig. 1. The Unified Texture Map (UTM) and Cleaned Mesh

3. Data Acquisition and Preprocessing

3.1. Data Collection

Over the last eight years we have collected a 3D longitudinal database of 3D videos for our research. A 3dMD face capture system is used, which uses structured light to capture a textured 3D mesh at a rate of 60 frames per second. The meshes contain around 55,000 triangles, and capture the front and sides (beyond the ears) of the subjects' faces. In this work, a set of 80 subjects who performed closed mouth smiles was used. The set was subdivided into two groups according to age: young people (Group 1: ages 15-30 years) and adults (Group 2: ages 31-60 years). Both groups contain 40 subjects equally split between males and females. The mesh data undergoes several preprocessing steps that are necessary to remove artifacts and improve subsequent processing steps.

A fully automatic, robust preprocessing pipeline is used that cleans the 3D meshes and creates of a single-view texture map (UTM) from the raw data provided by the capture system which produces multi-view texture maps and meshes with duplicate vertices. The cleaning steps include removing non-manifold edges and vertices, along with small components and isolated vertices, and the holes created from the removal of these imperfections are identified and filled[26,27]. The UTM as shown in Fig. 1 allows for the modification of vertices without incurring texture issues. After applying this processing, tracking and registration are carried out to create corresponding meshes and texture maps. The tracking and registration approaches are described in the following sections.

3.2. Facial Tracking and Registration

The tracking approach we use requires the user to annotate a single mesh from the sequence, clicking on the ordered sequence of 41 facial feature points: eye corners, centre of upper eyelids, cheek centre, nose tip, lip corners, and contour of face. These points are then automatically tracked following the approach proposed by Vandeventer[26,27], and enable us to subsequently analyse the facial dynamics as shown in Fig 2.

In each frame of a sequence, the face should to be aligned before feature extraction to eliminate any effects of head movement. This is carried out using Procrustes analysis to determine the rigid transformation.

3.3. Temporal Segmentation

A smile can be defined as the upward movement of the lip corners, which corresponds to Action Unit 12 in the facial action coding system (FACS)[28].

Fig. 2. Tracked Smile Sequence Frames

Most facial expressions are composed of three non-overlapping temporal phases, namely: the onset, apex, and offset. Onset is the initial phase of a facial expression and it defines the duration from neutral to expressive state. Apex phase is the stable peak period (which may be short in duration) of the expression between onset and offset. Offset is the final phase from expressive to neutral state. Following the registration step, the onset, apex, and offset phases of the smile are detected using the approach proposed by Dibeklioğlu et al.[23]. Smile amplitude is estimated as the mean amplitude of the right and left lip corners, normalized by the length of the lip. Let $D_{lip}(t)$ be the value of the mean amplitude signal of the lip corners in frame t.

$$D_{lip}(t) = \frac{\rho\left(\frac{l_{18}^1+l_{24}^1}{2}, l_{18}^t\right) + \rho\left(\frac{l_{18}^1+l_{24}^1}{2}, l_{24}^t\right)}{2\rho\left(l_{18}^1, l_{24}^1\right)} \tag{1}$$

where l_i^t denotes the 3D location of the i^{th} point in frame t, and ρ is the Euclidean distance between two points. Temporal smoothing is applied to l_i^t using a Robust Local Regression smoothing method[29]. Then, the onset phase is determined by the longest continuous increase in D_{lip}. Similarly, the offset phase is detected as the longest continuous decrease in D_{lip}. The phase between the last frame of the onset and the first frame of the offset defines the apex. Smile amplitude is computed, and polynomials are fit to the resulting function for smoothing purposes. Subsequently, onset, apex and offset are selected on the smoothed curve[23,24,22]. See Fig. 3 for examples of automatic segmentation and smoothed smiles; the left blue line is the first frame of the smile onset, the section between the two red lines is the apex phase, and the right blue line delimits the last frame of the smile offset.

3.4. Dynamic Feature Extraction

To provide more insight on the patterns of smile dynamics, a set of dynamic features are extracted from three phases of the mouth region. In fact, in our procedure we used the same dynamic features that were adopted by Dibeklioğlu et al.[23]. The dynamic features extracted from the lip region are grouped by the temporal phases (onset, apex, offset) as can be seen in Table 1. In addition to smile amplitude, speed V and acceleration A signals are extracted by computing the first and second derivatives of amplitude, respectively:

$$V(t) = \frac{dD}{dt}, \tag{2}$$

$$A(t) = \frac{dV}{dt} \tag{3}$$

The features are extracted separately from each phase of the smile. In order to obtain more detailed analysis of feature dynamics, each phase is further divided into increasing and decreasing segments; symbols $(+)$ and $(-)$ are used to denote the type of segments. For example D^+ (respectively D^-) represents the increasing (respectively decreasing) segments in D, where D refers to amplitude signals. The number of frames is represented as n, and the frame rate of the video by ω.

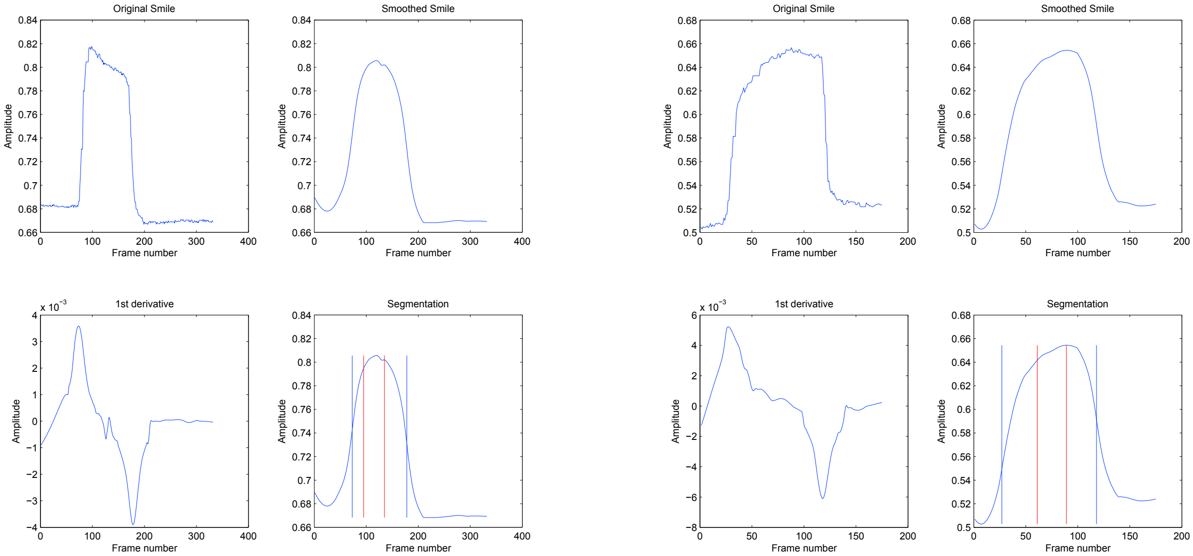

Fig. 3. Temporal segmentation of smiles, left (female), right (male)

Table 1. Dynamic Features used in the study.

Dynamic Features	Description
Duration	$\left[\frac{n(D^{+})}{\omega}, \frac{n(D^{-})}{\omega}, \frac{n(D)}{\omega}\right]$
Maximum Amplitude	$max(D)$
Mean Amplitude	$\left[\frac{\sum(D)}{n(D)}, \frac{\sum(D^{+})}{n(D^{+})}, \frac{\sum(D^{-})}{n(D^{-})}\right]$
Standard deviation of Amplitude	$std(D)$
Max Speed	$\left[max(V^{+}), max(\mid V^{-} \mid)\right]$
Mean Speed	$\left[\frac{\sum(V^{+})}{n(V^{+})}, \frac{\sum(V^{-})}{n(V^{-})}\right]$
Max Acceleration	$\left[max(A^{+}), max(\mid A^{-} \mid)\right]$
Mean Acceleration	$\left[\frac{\sum(A^{+})}{n(A^{+})}, \frac{\sum(A^{-})}{n(A^{-})}\right]$

3.5. Static Features Extraction

The medical literature describes studies to evaluate smiles in different age groups. Chetan et al.[17] considered the perioral zone at rest and smiling when analysing smiles in different age groups by using video records of these subjects. A cross-sectional study was performed to measure the characteristics within groups of different ages and determine whether they were significantly affected by gender. The four linear measurements listed in Table 2 were computed from rest and smile photographs.

Table 2. Static Measurements used in the Chetan et al. [17] study

Static Measurements	Description
1. Upper lip length	Distance measured between subnasale and stomion superius.
2. Upper lip thickness	Distance measured between labrale superius and stomion superius
3. Outer intercommissural width	Distance measured between right and left outer lip corner
4. Commissural height	Distance measured from horizontal line passing through subnasale to outer commissure

In our approach, we automatically extract two of these measurements (3 and 4; Table 2) as static features, their values are computed for one rest and one smile frame and averaged. The percentage change from the corresponding distance in the rest position can be considered as a normalisation to avoid anatomical variation due to physical size differences between the individuals. The results obtained are shown in Table 4.

4. Age Analysis Approach

Generally, a preprocessing stage is required to remove holes, spikes, and to fill missing parts as a result of the capture process. First the 3D capture of a smile is obtained by using the 3dMD system, cleaned to create a single-view texture map (UTM). Then, detection of some face landmarks is usually required to separate the face region from the unwanted parts of the obtained face scan. Facial features points are located in the first frame, and tracked during the rest of the smile video using an automatic tracking method, These points are used to calculate displacement signals of lip corners. Finally, pose normalization is also required to minimize overall deviations between the landmarks sets. This can be achieved by Procrustes analysis of the landmark sets through translation, rotation and scaling. Fig. 4 shows the proposed method followed in this paper.

Segmentation of the smile is performed automatically by detecting the main positive and negative peaks in the first derivative of the smile amplitude. The first positive peak in the first derivative is selected as the first frame of the onset phase. Likewise, the last negative peak determines the last frame of the offset phase. The phase between the onset and offset contains the peak of the smile. It is determined by finding the end of the onset and the start of the offset. The former is estimated by starting at the first frame of the onset and then repeatedly moving to the following frame while the smile amplitude decreases until the first derivative drops below an experimentally determined threshold. The end of the peak smile phase is found in an analogous manner. Each phase is divided into increasing and decreasing segments to provide more detailed analysis of the feature dynamics. Static and dynamic features were extracted separately to evaluate smile in different age groups. We have compared the results and showed that 3D facial dynamics provide more useful information than static features for the characterisation of smiles. A two-factor (age groups and gender) analysis of variance (MANOVA) using general linear models is performed. The data was analysed using the SPSS Statistical Package and descriptive statistics (means and standard deviations) were obtained for groups. The groups were then compared to evaluate the effect of age in men and women separately by analysis of variance. The significance level was set at 0.05.

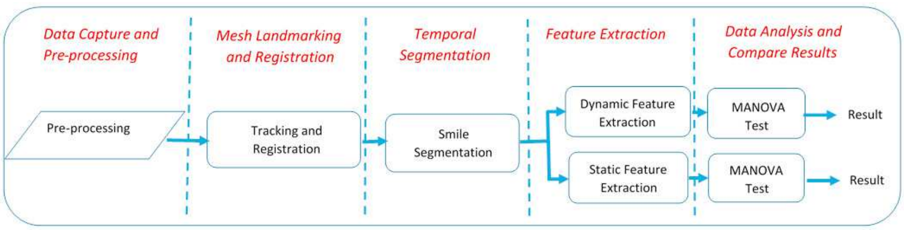

Fig. 4. The Proposed Method

5. Results

The results shown in Table 3 analyse differences between gender and age groups. There are significant differences $(p < 0.05)$ between the male and female groups of young people for the maximum and mean amplitude of their smile. Also, the maximum acceleration feature in group 1 was more significant $(p < 0.05)$ than in group 2 between genders. The mean acceleration feature is significant $(p < 0.05)$ in group 2 between genders (Table 3). Interestingly, there were also significant $(p < 0.05)$ differences in gender in *all* dynamic features of the smile.

Further investigation has shown that although there are clear differences between age groups they are not statistically significant. This is probably because of the relatively small sample size or due to the existence of extreme values. The exception was for the maximum amplitude with a significant difference for males in group 1 compared to the age group 2 (Table 4).

Table 5 shows that given the sample size, static features do not provide statistically significant discrimination between gender or age groups. In contrast we have shown that dynamic features are more powerful, given that they are statistically significant even for the small data set.

Our experiments show that temporal facial information — the fusion of onset, apex and offset phases of smile of lip region — provides discriminative information for different age groups and gender differences. While our sample range is relatively small, our results still produce statistically significant results and support previous results[17,23] on larger data sets but using 2D static and 2D dynamic data respectively that have demonstrated the powerful of dynamic features and have been used in many applications. Our experiment demonstrates that 3D video has good potential for further investigation. 3D data has a distinct advantage in that all measurements are actual physical (3D) distance measures that do not suffer from (2D) projective distortion, yielding more accurate and reliable measures. Further experiments will evaluate this aspect.

In summary, the results show that the most significant differences between young people and older adults are in the maximum acceleration of lip corner movements during smiles for both males and females. The results also show that the old adult people have less amplitude of smile. This conforms with clinical studies that have found that the elasticity of a person's lips decreases with age[30,12].

Table 3. Descriptive Statistics and Significance of Mean Differences of Dynamic features Between Males and Females within age groups

		Gender				
		Male		Female		
Dynamic Features	Groups	Mean	SD	Mean	SD	*P* Value
Duration	Group 1	0.29083	0.13195	0.36083	0.15776	0.427
	Group 2	0.27416	0.13759	0.33333	0.15700	0.644
Maximum Amplitude	Group 1	0.75227	0.15175	0.89415	0.43618	**0.025**
	Group 2	0.66543	0.11548	0.72926	0.11722	0.614
Mean Amplitude	Group 1	0.72216	0.14594	0.85037	0.42517	**0.028**
	Group 2	0.63976	0.11560	0.69705	0.10695	0.846
Standard deviation of Amplitude	Group 1	0.25546	0.21776	0.34695	0.19738	0.770
	Group 2	0.22103	0.12977	0.26803	0.16529	0.179
Max Speed	Group 1	0.01638	0.017335	0.14634	0.11672	0.090
	Group 2	0.02678	0.05162	0.01024	0.00841	0.062
Mean Speed	Group 1	0.00354	0.00302	0.00418	0.00301	0.883
	Group 2	0.00499	0.00759	0.00301	0.00237	0.095
Max Acceleration	Group 1	0.01705	0.022772	0.00995	0.01012	**0.014**
	Group 2	0.01107	0.01269	0.00724	0.00681	**0.029**
Mean Acceleration	Group 1	0.00035	0.00115	0.00015	0.00049	0.387
	Group 2	0.00283	0.00871	0.00005	0.00030	**0.026**

Table 4. Comparisons of Dynamics features *Group 1 vs Group 2* within Males and Females

Dynamics features	Male (*P value=0.05*)	Female (*P value=0.05*)
Duration	0.698	0.584
Max Amplitude	**0.049**	0.111
Mean Amplitude	0.055	0.126
Standard deviation of Amplitude	0.547	0.178
Max Speed	0.398	0.180
Mean Speed	0.511	0.186
Max Acceleration	0.211	0.327
Mean Acceleration	0.505	0.456

Table 5. Static measurements results obtained between male and female within age groups

		Male		Female		
Static Measurements	Groups	Mean	SD	Mean	SD	*P* Value
Outer intercommissural width	Group 1	0.010277	0.000176	0.010216	0.000111	0.202
	Group 2	0.010276	0.000185	0.010377	0.000370	0.278
Commissural height	Group 1	0.102441	0.001271	0.102914	0.002603	0.470
	Group 2	0.102424	0.000664	0.103089	0.001341	0.054

Table 6. Comparisons of Static measurements between *Group 1 vs Group 2* within Males and Females

Static measurements	Male (*P value=0.05*)	Female (*P value=0.05*)
Outer intercommissural width	0.985	0.168
Commissural height	0.960	0.605

6. Conclusion and Future Work

Based on the results, it can be concluded that smiles change with age and their characteristics differ between males and females. We have studied the influence of gender to conclude that gender plays a crucial role in facial feature analysis. We have analysed the rich sources of information present in the 3D dynamic features of smiles to provide more insight on the patterns of smile dynamics. The source of temporal information that are investigated are various dynamics of lip movement analysed to extract the descriptive features. We evaluated the dynamic features on closed mouth smiles of 80 subjects of both genders. In future investigations, it is possible to use different regions of the face such as the eyelids and cheeks to evaluate which dynamic features are more related to age, and it would be possible to apply our methodology to investigate other factors beyond age, such as race and medical conditions[31,32,33,34].

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