Recognition of Genuine Smile as a Factor of Happiness and its Application to Measure the Quality of Customer Retail Services

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Abstract: *A method to distinguish between genuine and posed smiles by their description in the form of lips displacement signals, different in shape, and then performing the classification in the frequency domain has been proposed.*

The demonstration of FaceAnalyzer program applied to the analysis and digitization of video records and retrieving the human face parameters to calculate and visualize the Smile-Index and its components over time and control the quality of customers' satisfaction with retail services is presented.

Keywords**:** genuine and posed smiles, classification, lips displacement, spectral function, Smile-Index.

1. INTRODUCTION

The analysis and classification of facial emotional expressions have been an active research area since the Facial Action Coding system (FACS) was proposed by Ekman [1]. Since the literature on automated facial expression recognition is extensive, we refer the reader to one of the comprehensive surveys [2].

A smile, as one of the basic emotional states have studied by psychologists for a long time. They investigated the correspondence between observer estimation of smiles and the morphological and dynamic characteristics of these face expressions. Generally, a smile can be recognized as the upward movement of the lip corners, which corresponds to Action Unit 12 (AU12) in FACS [1]. However, many researchers tried to associate morphological characteristics of true smile with the presence and activation of Orbicularis oculi (AU6). One of the known researchers from mid-nineteenth century Guillaume Duchenne claimed that smiles resulting from felt joy (so-called genuine smiles) are characterized by the presence of AU6 and in the posed smiles it couldn't be controlled voluntarily [3]. Later Ekman calculated that only 10% people can fake the enjoyment of a smile and initiate the element AU6 spontaneously, thus having the ability to fake a smile or to produce the posed smile.

However, there is still significant debate regarding whether AU6 must be the necessary condition to fix the genuine smiles that are also called spontaneous smiles. Several researchers reported observing high proportions of posed smiles that fit the Duchenne smile criteria [4]. To determine the type of smiles a number of dynamic characteristics of emotions has been studied. Dynamic characteristics include duration, intensity, speed, and lip corners symmetry [5].

In terms of dynamics, smiles can be composed of three non-overlapping phases; the onset (neutral to expressive), apex, and offset (expressive to neutral), respectively. Several years before [6] and recently [4,5] many researchers performed studies devoted to the classification of smiles in accordance with their temporal characteristics.

In accordance with the studies mentioned above, the average duration of a genuine smile can range from 0.5 seconds to 4.0 seconds, while posed smiles can be either longer or shorter. Previous studies have reported differences in duration for the various phases of genuine and deliberate expressions [4]. Also genuine smiles tend to have a slower onset speed and longer onset duration than posed smiles. Considering the onset phase duration, genuine smiles can range between 0.5 and 0.75 seconds. Spontaneous smiles produced in a social context average an onset duration of 0.50, 0.59, and 0.67 seconds [4]. Finally, Schmidt et al. [6] observed greater onset and offset speeds, amplitude (displacement) of movement, and offset duration in posed smiles.

Interestingly, several studies indicated that deliberate Duchenne smiles were rated as more intense with average value 3.37 than spontaneous Duchenne smiles, where it has value 2.85 [4]. These finding suggests that individuals who fake smiles are capable of control their facial movements, and tend to express exaggerated smiles that are more intense than genuine smiles. Regarding temporal asymmetries, these authors found no differences between genuine and posed smiles in terms of asymmetries in onset or offset duration.

Previous research [7] has considered about 25 features to investigate the differences between genuine and posed smile. At the same time, many of these features were difficult to explain from a psychological point of view. In recent research [4] authors extracted duration, speed, intensity, symmetry, and irregularity of the lip corners to find the difference between genuine and posed smiles.

However, often so many parameters are not necessary due to the existence of a correlation between them. In this paper, we will perform an analysis of the temporal characteristics of two smiles types based on one parameter-lip corner displacement that is time dependent, and perform their classification in the frequency domain.

The rest of the paper is organized as follows. Section 2 introduces the state-of-art for classification of posed and genuine (spontaneous) smiles in the frequency domain of facial motion timing signals for the two smiles types. Section 3 demonstrates the application of FaceAnalyzer program developed and used to perform statistical experiments with the use of the UvA-NEMO Smile Database. Section 4 describes the application of the developed algorithm to evaluate the so-called Smile-Index (SI) of customers' satisfaction with retail services in urban areas. Finally, Section 5 concludes the paper.

2. CLASSIFICATION OF GENUINE AND POSED SMILES IN FREQUENCY DOMAIN

The time signals of genuine and posed smiles will be denoted as $s_1(t)$ and $s_2(t)$ respectively, and their corresponding spectral functions as $S_1(j\omega)$ and $S_2(j\omega)$. To study the properties of signals, we will assume in the beginning that they are continuous in time.

To perform signals $s_1(t)$ and $s_2(t)$ classification we will distinguish them by form. We assume that signal $s_1(t)$ is a single Gaussian pulse, i.e.

$$s_1(t) = ae^{-(t-b)^2/d}. \quad (1)$$

where the constants a, b, d have corresponding meanings of amplitude, average value and signal attenuation value. To use the well-known representation of the Gaussian signal, the following representation of $s_1(t)$ is applied

$$S_1(t) = \frac{P}{\sigma\sqrt{2\pi}}e^{-t^2/2\sigma^2}. \quad (2)$$

Then the introduced constants will have the following values: $a = \frac{P}{\sigma\sqrt{2\pi}}$; b=0; $d = 2\sigma^2$.

Next, we define the duration of signal at half of its peak value FWHM (Full width at half maximum) as t_i. We omit the coefficient P before the exponent in (2) and find the time coordinate t_0, in which (2) will have a value of 50% of the maximum: $0.5s_1(0)$.

$$e^{-t_0^2/2\sigma} = 0.5s_1(0) = \frac{1}{2}. \quad (3)$$

To obtain formula (3), we adopted $a = 1$ and $b = 0$ in the original signal representation. After performing simple mathematical transformations, we obtain the duration of $s_1(t)$ at FWHM:

$$t_i = 2t_0 = 2\sigma\sqrt{2\ln 2} \approx 2.3548\sigma. \quad (4)$$

It is also known [9] that a spectrum of Gaussian signal is also a Gaussian function. Thus, spectral function or spectral density $S_1(j\omega)$ is represented as

$$S_1(j\omega) = \frac{a}{2\sigma^2}e^{-\omega^2\sigma^2/2}. \quad (5)$$

The function in (5) is symmetric with respect to zero and monotonically decreases for a positive argument. The spectral function $S_1(j\omega)$ for the posed smile behaves in time quite differently and will be represented in time domain as a trapeziodal signal:

$$s_1(t) = \begin{cases} \frac{A}{t_s}t + c, -t_s \le t < -\frac{t_a}{2} \\ A, \; -\frac{t_a}{2} \le t < \frac{t_a}{2} \\ -\frac{At}{t_s} + c, \; \frac{t_a}{2} \le t < t_s \end{cases}, \quad (6)$$

where A is a peak value of the signal, t_s is the duration of pulse slopes (pulse front and cutoff of a signal), c is a constant that determines the steepness of the signal front, and t_a is the duration of the pulse flat top, as depicted in Fig.1. The parameters of the trapezoidal pulse, corresponding to the posed smile, take approximately the following values [4] t_s=0.7, t_a=1.6, T_0=3 seconds, leading to parameter FWHM=2.3 seconds. However, the total duration of Gaussian pulse defining the time of a genuine smile was [4] T_g=5 seconds. The relationship between these parameters is easy to find given (6).

In this study, we assume that a posed smile is created with the help of a constant rate of increase or decrease of the facial muscles tension, and then held with the help of stretched lips. This is a somewhat simplified model, but reflects the process of posing and is used in this study.

Next, using the properties of the Fourier Transform (FT) and using the differentiation of a rectangular pulse we can find a spectral function of a trapezoidal signal in the following form [9]

$$S_2(j\omega) = At_i\frac{\sin(\omega t_i/2)}{\omega t_i/2} \cdot \frac{\sin(\omega t_s/2)}{\omega t_s/2}. \quad (7)$$

The spectral density $S_2(j\omega)$ of signal $s_2(t)$ is similar to the spectrum of a rectangular pulse with the presence of slightly suppressed side lobes, which are appeared due to the zeros of the spectral function (7). The characteristic expressions of spectral densities functions $S_1(j\omega)$ and $S_2(j\omega)$ can be found in [9], however, we will look at their graphs below when conducting the experiments with real signals.

Now, given the differences in the behavior of $S_1(j\omega)$ and $S_2(j\omega)$, we can propose an algorithm for their classification in the frequency domain using the Discrete Fourier Transform (DFT) of the discretized versions $g_1[n]$ and $g_2[n]$ of the original signals $s_1(t)$ and $s_2(t)$.

The standard expression of DFT is defined by the formula (8) and can be used to approximate the spectral function $S(j\omega)$ of a given continuous in time signal $s(t)$ (9) that must be time limited or truncated with some duration T_0.

$$G[k] = \sum_0^{N-1} g[n]e^{-i2\pi\frac{kn}{N}}. \quad (8)$$

$$S(j\omega) = \int_{-\infty}^{\infty} s(t)\, e^{-i2\pi\omega t}dt. \quad (9)$$

In fact, the original signal is sampled in time with sampling period T_s (sampling rate f_s=1/T_s) and looks like sequence $g[n]$ of length L. Hence, if rate f_s and length of $s(t)$ f_0=1/T_0 are high enough, then DFT (8) is approximately a sampling of the regular Fourier Transform starting at f=0 in steps of Δf=f_0, scaled then by sampling rate f_s, i.e.

$$G_N[k] = \frac{G[k]}{N} \approx \frac{f_sS(kf_0)}{N}. \quad (10)$$

Thus, based on the proposed signal models, an analysis of their spectral properties, taking into account the use of DFT of their discrete copies $g_i[n]$, the algorithm for their classification may include the following steps.

1. With the use of formula (1), obtain the discretized signals $g_i[n]$ of input length L_i (i=1,2) corresponding to one of two classified signal types.

2. Convert the length of $g[n]$ to N, that is the next power of two from the original signal length L_i. Perform its DFT using (8) and find frequency components $G_N[k]$ for k=1,N.

3. For each element $G_N[k]$, starting from k=1, check G_N decrease and find a ratio

$$r = G_N[k+1]/G_N[k]. \qquad (11)$$

4. If $r < 1$ then signal $g[n]$ belongs to class 1. If not, then increment k. If k=N-1, then signal belongs to class 2.

The application of the algorithm allows not only to perform the classification, but also to measure the duration of a smile signal.

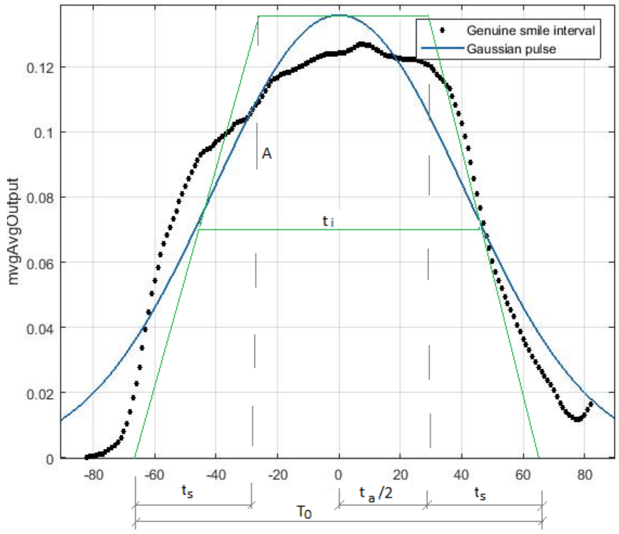

Fig.1 –Recorded interval, model of genuine and posed smile

3. FACEANALYZER PROGRAM FOR RECOGNITION OF GENUINE AND POSED SMILE

We have developed the FaceAnalyzer Program (FAP) [8] based on OpenFace tool [10] to carry out the study of human characteristics and perform the analysis, recognition and verification of human biometric data, elements of his emotions by capturing images and video, features extraction and data processing. OpenFace is one of the best toolkits performing the facial landmark detection, head pose estimation, facial action unit recognition, and eye-gaze estimation with available source code for both running and training models. The tool OpenFace uses Conditional Local Neural Fields (CLNF) to perform 68 Facial Landmark detection (see Fig.2) and tracking. CLNF is an instance of a Constrained Local Model (CLM) that uses Point Distribution Model (PDM) which captures landmark shape variations and patch experts (PE) to capture local appearance variations of each landmark.

To track landmarks in videos Baltrusaitis et all [10,4] initialize the CLNF model based on landmark detections in previous frame. If tracking has been failed, the model was reinitialized using the dlib face detector. The modified OpenFace tool allows to detect multiple faces in an image and track multiple faces in videos. This tool is also able to extract head pose information by the use of a pseudo 3D representation of facial landmarks using orthographic camera projection. Proposed landmark detector can learn non-linear and spatial relationships between the input pixels and the landmark being aligned. At this stage, the model is being improved taking into account the reliabilities of each patch expert.

Despite the fact that OpenFace uses both 2D and 3D face elements representation, we chose a simpler 2D model for face tracking and defining the landmarks on it. By determining the lengths of the displacement vectors of the lips extreme points (Landmarks 48 and 54 in accordance with Baltrusaitis numbering [11] as in Fig.2), it is possible to obtain a discrete time signal corresponding to the average displacement during the appearance of a smile. By the analogy with [4,7] we have performed the displacement normalization and obtained a modified formula for its average value:

$$D_l(t_k) = \frac{\left[\rho(l_{48}(1),l_{48}(k))+\rho(l_{54}(1),l_{54}(k))\right]/_2}{\rho(l_{48}(1),l_{54}(1))}, \qquad (12)$$

where $\rho(l_m(k+1), l_m(k)) = \sqrt{\Delta x_{k+1,k}{}^2 + \Delta y_{k+1,k}{}^2}$ is a vector length defined with the use of Euclidean distance for the position of landmark at time instants k and $k+1$.

This expression is somewhat different from the formula used in [4], and allows to consider the average displacement relative to the initial size of lips. However, this value is more convenient and independent of the face size.

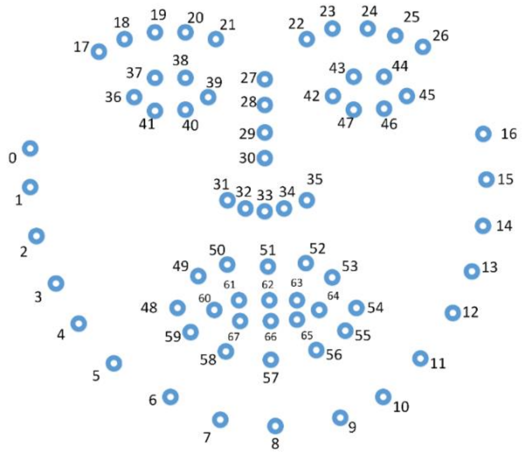

Fig.2 – Landmarks numbering in OpenFace tool

Further, using FAP and formula [2], the discrete values of lip element displacement for various frames were obtained. We have used the UvA-NEMO smile database, where each video episode contained only one smile, without any other emotions [7]. Smile database UvA-NEMO was prepared to analyze the dynamics of genuine and posed smiles. The database consists of 1240 smiling videos with approximately the same ratio derived from 400 subjects (185 women and 215 men, in the age range of 8-

76 years). Color videos at a rate of 50 frames per second were recorded at a resolution of 1920 × 1080 pixels with controlled lighting. It is necessary to note that a number of subjects in the process of a smile were “shaking” their heads, which led to significant “jumps” in the calculated of the lips displacement value (12) relative to the initial frame. To compensate this factor, in our study, a correction was made by using 2D rotation matrices similar to [7].

Every smile comes from the neutral emotional state of the subject. Using FAP and recorded data in csv file, we were able to capture the discrete signals corresponding to the state of a smile. An example of the genuine smile signal (dark line) and the same signal passed through the 8-element averaging filter (light line) is shown in Fig. 3. To calculate the required discrete signals formula (12) has been used. FA program allowed to calculate the intensity of the Action Units values, involved in the “smile creation” simultaneously with the visualization of the signal timing chart (see Fig.3). The FAP menu allows to display the required signal in a frame by frame mode with the selected delay, as well as to analyze each frame separately.

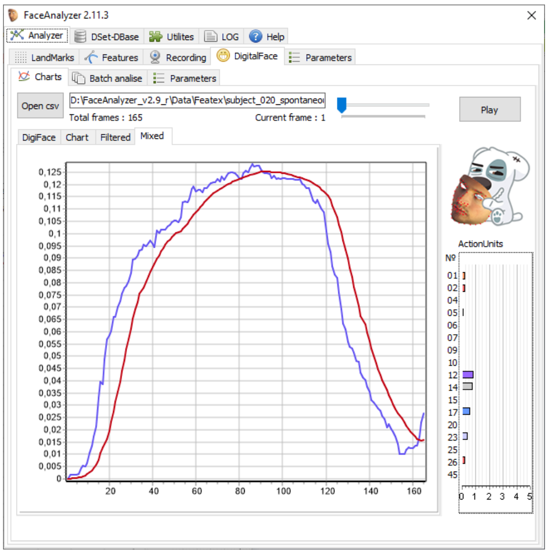

Fig.3 –Time signal received by FAP for posed smile

Then the discretized versions $g_1[n]$ and $g_2[n]$ of genuine and posed smiles of original time signals had been recorded and the proposed algorithm for their classification with the use of frequency components $G_N[k]$ was applied. The graphs of the first eight normalized spectral components obtained for genuine $G_g(k)$ and posed smile $G_p(k)$ with lengths N_1=256 and N_2=128 are shown in Fig.4 (continuous and dashed line respectively).

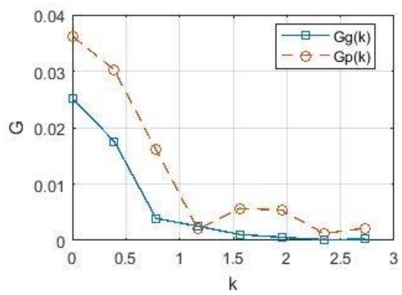

Fig.4 – Frequency components for two smile types

The application of the classification algorithm described above with a threshold of r = 0.002 allowed to distinguish the posed smile from genuine one in the frequency domain.

Further, the procedure of smile type classification and evaluation allow us to calculate the quality of service in retail outlets based on special index, which will be discussed in the next section.

4. SMILE-INDEX AND THE QUALITY OF CUSTOMER RETAIL SERVICE

When we are satisfied with the quality of service and salespeople, managers smile at us sincerely, we instinctively smile back. The more customers smile, the higher the quality of service. Measuring the proportion of time during which customers smile at the point of contact, we get an indicator of customer-oriented staff, which is also an integral indicator of the quality of customer service. An example of such an indicator is the Smile-Index (SI), supported by the decision of Emotion Monitor [12]:

$$SI(Th) = \frac{[T_g(happy) + T(neutral)]/2}{T(total)}, \qquad (13)$$

where Th – a threshold, characterizing the quality of perception or QoE (Quality of Experience) and usually having 5 gradations: from "unacceptable" to "excellent" as shown in Table 1.

The time intervals in formula (13) mean following: T_g (happy) - a period of time during which the level of happiness caused by genuine smile was greater than the value of Th; T(neutral)- a period of time during which the level of happiness was less than the value of Th, but greater than Th/4; T(total) - the period of time for which the measured values of the level of happiness exist.

Table 1. The gradations of QoE

Category	SI (*Th*)
Excellent	1.0Th
Good	0.94Th
Fair	0.85Th
Bad	0.7Th
Unacceptable	0.0Th

Compared with the characteristics of quality of service, measured using traditional indicators, Smile-Index has several important advantages.

1. Smile-Index is a positive motivator for staff. Positive motivation is a reward for achievement, not punishment for non-fulfillment. Smile-Index motivates staff not only to perform their duties well, but also to make customers happy.

2. The ability to obtain an accurate information about the quality of service without the involvement of front line staff. When using the usual indicators of evaluation in surveys usually takes no more than 10% of customers.

3. The ability to assess the quality of services through the "eyes" of different age and gender groups, which simplifies the management of the quality of services. The expectations of different age and gender groups can vary greatly.

4. To assess the quality of customer service it is not necessary to install additional equipment, because almost any company is equipped with video surveillance system.

To calculate SI, during the specified time we continuously measure the level of Happiness of the target audience and obtain a set of every frame levels of Happiness values. In some periods of time, surveillance cameras may not capture customers. Therefore, the time for which we have measurements is always less than or equal to the time of measurement. The time for which we have measured values is the total time *T*=*T*(*total*).

However, we need to set a threshold *Th* for the level of happiness, which depends on several factors of customer service: region, target audience, etc. Then the value *Th* (usually within 1 minute) determines the required (good) quality of service. We will assume that the level of happiness in the range from *Th* to *Th*/4 corresponds to the acceptable (tolerable) quality of service. If the level of happiness is less than *T*/4, then the quality of service is poor. Hence, all obtained values of the *level of happiness* can be divided into 3 groups: 1-st group for which all time intervals has index value greater than or equal to *Th* (*Happy* time); for the 2-nd group we assign all values less than *Th*, but greater than *Th*/4 (it determines *Neutral* period of time during which the quality of service was tolerable); 3-d group includes all the remaining time values (*Upset* time). Generally, these groups determine the time when customers are satisfied with service, tolerant of its quality and dissatisfied with it.

Measuring Smile-Index, any company will know the level of quality of service in relation to the leader, and can evaluate the effectiveness of advertising, the friendliness of the front line staff, etc. Obviously, Smile-Index can be used not only to determine the quality of service, but also to evaluate the other processes related to service, advertising, and other types of human activity.

To estimate SI, it is recommended to use Table 1 of the threshold values *Th* coefficients. However, for managing the quality of customer service, not only the SI value is necessary, but also the thresholds themselves are important, because on the basis of them Smile-Index is calculated. Generally, to find the appropriate *Th* values and determine the dependence of threshold value on the positive emotions of a customer, the necessary statistics is required, which we have obtained from UvA-NEMO Smile database [7]. Considering that a spontaneous smile demonstrates true happiness, we selectively experimented with video recordings, containing spontaneous smiles. With assistance of FAP tool, we have performed preprocessing of selected video records with extracting the intensities of AU parameters for each frame. Using this data, we were able to calculate the desired *happiness threshold* as an estimated weighted average which can be defined as

$$\widehat{Th}_a = \sum_{i=1}^{n} \bar{I}_i(AU) w_i \;/ \sum_{i=1}^{n} w_i, \qquad (14)$$

where w_i,- weights that determine the contribution of the intensity of each action unit AU in each frame where they are present, $\bar{I}_i(AU)$ is the average of intensity for the *i*-th AU value. It is known [9] that a standard error of weighted mean with unit input variances gives the result variance $\sigma_{Th_a} = (\sqrt{\sum_{i=1}^{n} w_i})^{-1}$, that characterizes the use of weights in the average calculation (14).

With the use of FAP and UvA-NEMO Smile database we have performed the statistical experiments to find the *threshold of happiness* calculated using formula (14). For this purpose, we obtained the intensity values of all AUs, averaged over all *n* available records of spontaneous smiles in data base, and the corresponding weights w_i of these AUs averaged over all frames for each video being analyzed.

Hence, using the found threshold Th_a, it is easy to calculate the level of happiness and the Smile-Index value in each frame of the test video recordings using (13) and to determine the service category according to Table 1. In our setup we have considered that time of measurements is equal to the observation time determined by the duration of the video, consisting of a set of frames.

With the help of the developed FA program, we implemented the calculation of Smile-Index with different thresholds, which can be selected by operator who performs the analysis.

The graph (Fig. 5) presents an example of the FAP work during video processing with the presence of a genuine smile recorded by the author of Open-Face tool [11]. In the upper part of the figure, the graphical dependence of the Smile-Index changing its values with respect to time (frame number) is shown, and in the lower part - a dynamic histogram that defines the above states ("happiness", "neutral", and "upset") is given. With the use of temporal (frame by frame) presentation of these states it becomes possible to determine not only the achieved value of SI during the observation time, but also the distribution of its components over time.

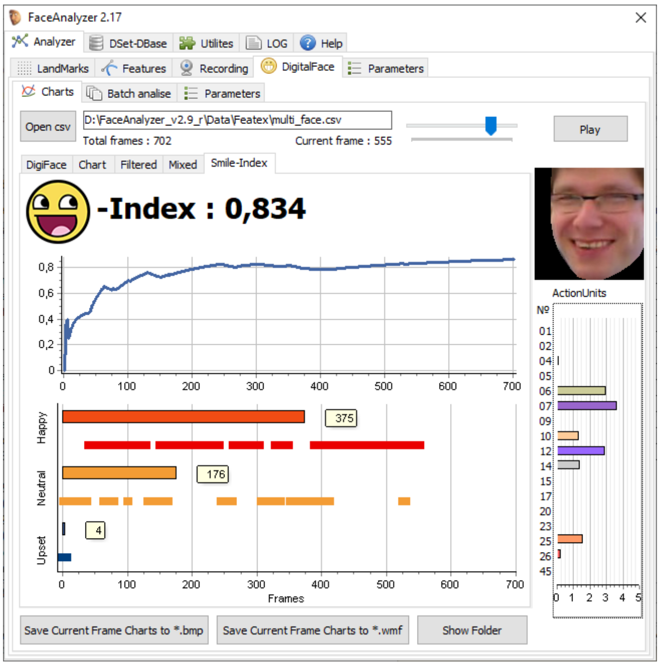

Fig.5 – Smile-Index and diagrams of its components

Thus, the assessment of the authenticity of a smile in real time allows to "turn on" the Smile-Index meter only at the appropriate times and realize the objectivity of the retailers' quality service evaluation.

5. CONCLUSION

Earlier [13], we have carried out the diagnostics of students' emotional mental states to obtain features of a person expressiveness based on Smile-Index during the examination tests in order to optimize the educational process with recognition of five selected students' emotions based on the corresponding AUs.

In this paper, we have presented a smile classifier that can distinguish genuine and posed smile based on a comparison of the waveforms generated by the lip displacement in the frequency domain. In the proposed algorithm, we have used a Gaussian waveform model, reproducing a genuine smile and a trapezoidal signal model corresponding to a posed smile. Due to the fact that these signals were obtained by frame-by-frame calculation of lip displacement, we analyzed them using the Discrete Fourier Transform.

We assumed that a genuine smile is created by approximately the same slow stretching and relaxation of lips, while the posed one is generated by a faster process of lips moving and keeping them for a while in an extended state. A series of experiments confirmed the ability of the algorithm to recognize a genuine smile with an incorrect distinction with a sufficiently small classification error.

Further reduction of the recognition error is possible by using the analysis of the various smile signal phases, more accurate their signal polynomial approximation and increasing the length of a feature vector involved in the classification process.

We also demonstrated the characteristic of FaceAnalyzer Program, based on OpenFace tool and developed to perform different statistical experiments with still face images and videos. The new version of FAP has the enhanced functionality compared with work [8] and allows to perform the analysis and visualization of both static and dynamic biometric and emotional characteristics.

In addition, in our work, we have examined the application of the developed approach in recognizing a genuine smile to assess the quality of customer service on the basis of so-called Smile-Index, which allows us to determine the category of customer service on the basis of the selected threshold. To obtain the SI, we have performed an analysis of video records of UvA-NEMO Smile Database containing fragments with a genuine smile and found the average threshold value weighted over all videos and all AUs involved. The results showed that the main contribution to the value of the weighted intensity (threshold) has been done by the following values of AU types: AU6, AU7, AU12, AU14.

The proposed approach to genuine and posed classification and calculation of Smile-Index and its components over time allow to control the quality of customers' satisfaction with trade services without involving specialized equipment and personnel and optimize the structure of diversified companies working in the retail and services sector.

7. ACKNOWLEDGMENTS

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