Effect of Parameter Tuning at Distinguishing Between Real and Posed Smiles from Observers' Physiological Features

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Abstract. To find the genuineness of a human behavior/emotion is an important research topic in affective and human centered computing. This paper uses a feature level fusion technique of three peripheral physiological features from observers, namely pupillary response (PR), blood volume pulse (BVP), and galvanic skin response (GSR). The observers' task is to distinguish between real and posed smiles when watching twenty smilers' videos (half being real smiles and half are posed smiles). A number of temporal features are extracted from the recorded physiological signals after a few processing steps and fused before computing classification performance by k-nearest neighbor (KNN), support vector machine (SVM), and neural network (NN) classifiers. Many factors can affect the results of smile classification, and depend upon the architecture of the classifiers. In this study, we varied the K values of KNN, the scaling factors of SVM, and the numbers of hidden nodes of NN with other parameters unchanged. Our final experimental results from a robust leave-one-everything-out process indicate that parameter tuning is a vital factor to find a high classification accuracy, and that feature level fusion can indicate when more parameter tuning is needed.

Keywords: Physiological features · Real smile · Posed smile · Observers · Parameter tuning · k-nearest neighbor · Support vector machine · Neural network

1 Introduction

A smile is a multifaceted and multi-functional facial display that generally conveys positive feelings, such as enjoyment, warmth, appreciation, satisfaction, and so on. We refer to these as real smiles, and refer to conscious attempts to faithfully mimic these as posed smiles. We also know that people can smile in negative or neutral situations too, such as arrogance, sarcasm, acted, appeasement, or smile to hide something [1] including frustration and puzzlement. We refer to these negative and non-happy smiles as fake smiles, and refer to smiles that signify happiness as happy smiles. With the growing interest in emotion recognition and human centered computing, intelligent machines are being developed to determine people's affective behavior. The recognition of emotion from others' facial expressions is a vital and universal skill for social

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interaction [2], and smiles attract more attention than any other regions of faces [3]. Thus, developing a system that understands a smiler's affective state could be used in many situations, such as customer service quality evaluation, interactive tutoring systems, video conferencing, patient monitoring, verifying truthfulness during interrogation or hearings, border control or customs, and so on.

Previously researchers focused on smilers' faces and/or observers' verbal responses to distinguish between real and posed smiles. A computational technique is used to recognize real smile from smiler's facial features in [4] and reports 92.9% correctness. Ambadar et al. [5] scrutinize the characteristics of fake smiles along with their perceived meanings, and find that perceived meanings are related to specific characteristics. Calvo et al. [1] inspect perceptual, categorical, affective, and morphological characteristics to recognize happy smiles, and suggest that happy smiles are more likely to occur with congruent happy eyes and smiling mouth. Frank et al. [6] considers observers' self-judgments of happy smiles and notes a 56.0% average response rate. Hoque et al. [7] execute two experiments for classifying happy and fake smiles from smilers' facial features, and report 93.0% and 69.0% accuracies by classifiers and verbal responses respectively. Although observers may have certain impressions or feelings during face to face interaction, watching video clips or listening to music [8], it is not an easy task to distinguish happy and fake smiles from observers' verbal responses [6].

On the other hand, physiological signals have the advantage of immediately being affected by observing facial changes that cannot be posed voluntarily or assessed well visually [8, 9]. In this regard, many studies [10, 11, 12] have considered peripheral physiology to recognize facial behaviors. In this paper, we analyzed three physiological signals from observers – pupillary response (PR), galvanic skin response (GSR), and blood volume pulse (BVP) – to classify smilers' affective states into real or posed classes. We believe 'real' to be a more accurate characterization for our work than 'happy' as the datasets elicited smiles, so they are real but did not consistently test the subjects' emotional state so we cannot confidently say they were happy. The situation is similar for the smiles which are not real: the subjects were asked to smile, which is a posed smile, and not fake in the many possible reasons for which people can do a fake smile.

Pupillary responses can change due to memory load, stress, pain, light intensity, content of face to face interactions and so on. It has the advantage of needing no sensors to be attached to the observer, and certainly not to the smiler [10]. GSR is considered to be a strong physiological signal in emotion detection that measures electrical changes of human skin automatically [11], and has been used for this task previously [12]. BVP measures blood volume changes using infrared light through the tissues, and used as an indicator of emotional changes and affective processing that affects heart rate and pulse amplitude [13]. The temporal patterns of these physiological signals are useful while classifying real and posed smile observations. Six statistical features are extracted from each peripheral physiological signal in each observation and used to compute classification accuracy using a robust leave-one-out process. By robust we mean that in each run, we leave out all the samples collected from a particular subject, along with all other subjects' responses to that particular stimulus (a short video in this case). That is, we go beyond leave-one-subject-out, and use leave-one-subject-and-one-stimulus-out. Thus, our results are not only subject independent, but also stimulus independent. Our aim is to detect smilers' affective states by classifying smiler videos into real and posed, from observers' peripheral physiology based temporal features, using three classifiers, namely k-nearest neighbor (KNN), support vector machine (SVM), and neural network (NN). In this paper we thoroughly examine parameter settings.

2 The Method

We collected twenty smilers' videos chosen at random from four benchmark database. We processed them using MATLAB to convert into grey scale, mp4 format with each video lasting 5 s. The videos are presented in a balanced order, and physiological signals are recorded from each observer while watching these videos. The signals are smoothed, filtered, and normalized. Six statistical time domain features are extracted from each signal. Binary classifiers are employed to classify between real and posed smiles. The overview of this method is shown in Fig. 1.

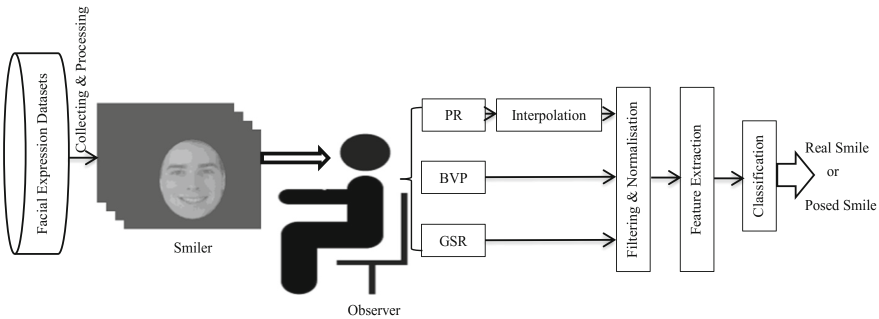

Fig. 1. Outline of the research.

2.1 Smile Videos

Ten videos were collected from UvA-NEMO [14] and MAHNOB [15] databases (five from each) where real smiles were elicited from smilers, by showing a sequence of funny or otherwise pleasant video clips. Ten videos were collected from MMI [16] and CK+ [17] databases (five from each) where posed smiles were created by smilers with experimenters asking or instructing them to display a smile. We used 4 databases to increase the variation in our stimuli. The collected videos were processed using MATLAB R2014b to make them uniform in size, format and duration. These are: fixed aspect ratio of 4:3 (Height = 336 pixels, Width = 448 pixels) with resolution of 72 dpi, grey scale, mp4 format, and lasting 5 s each. Frame rates are adjusted slightly to make each video's length be 5 s long. Luminance (128 ALU – Arbitrary Linear Unit) and contrast (32 ALU) of smilers are also adjusted and kept similar using the MATLAB SHINE toolbox [18]. Only faces of smilers are shown to the observers (see *Smiler* in Fig. 1), to avoid the side effect of light backgrounds on pupil dilation.

2.2 Observers

Twenty-four right-handed healthy volunteers (15 males, 9 females) participated as observers in the study, with mean age of 30.7 ± 6.0 (mean ± SD). All observers had normal or corrected to normal vision. They signed an informed consent form prior to their participation. Ethics approval was received from our Australian University's Human Research Ethics Committee, prior to performing the study.

2.3 Peripheral Physiology

Pupillary Response (PR): This physiological signal is measured from the eyes' responses that vary the size of the pupil. The primary function of this response is to control the amount of light reaching the retina. When luminance is controlled, then other influences on pupil size can be detected. Pupil dilation is the widening of the pupil and is controlled by the sympathetic nervous system and may be happening due to e.g. high curiosity. Constriction means narrowing the pupil, and that is controlled by the parasympathetic nervous system and may be happening due to less curiosity [10]. The magnitude of the pupillary response appears to be a function of the attention and curiosity required to perform a task. This is an involuntary signal that changes with any event observed by the subject, and recorded here using The Eye Tribe remote eye-tracker system (https://theeyetribe.com/), with a sampling rate of 60 Hz.

Blood Volume Pulse (BVP): A photoplethysmographic (PPG) sensor measures the change of blood volume that passes through the tissues over a given period of time, this is the BVP. A light-emitting diode is used to pass an infrared light through the tissues, and the returned light is proportional to the volume of the blood in the tissue. BVP signals are used as indicators of emotional response by measuring the change in peripheral physiology. It is possible to identify observers' or subjects' mental states by analyzing the variation of BVP amplitudes [13]. In this study, each observer's BVP signals are recorded from the wrist of the left hand at a sampling rate of 64 Hz using an Empatica E4 device (https://www.empatica.com/).

Galvanic Skin Response (GSR): Skin conductance, also known as electro-dermal response or psychogalvanic reflex, measures the electrical changes in human skin that varies with changes in skin moisture level (sweating). This is an automatic reaction that cannot be controlled voluntarily and reflects changes in the sympathetic nervous system, and is an indication of psychological or physiological arousal that can be used for affect detection or mental state recognition [11]. When an observer is more curious, skin conductance is increased; conversely, the skin conductance is reduced when an observer finds it easier (less stressful), e.g. to identify a smile video. The same Empatica E4 sensor as used in BVP recording is used here to record the GSR signals from the observer's left wrist, at the maximum sampling rate of 4 Hz.

2.4 Conduct of the Experiment

Each observer (subject) fills in a consent form for their voluntary participation. A 15.6" ASUS laptop and a normal computer mouse are peripherals for interaction between the observer and a laptop running the web-based tool showing the smile videos. The chair of the observer is moved forward or backwards to adjust the distance between the observer and eye tracker. Observers are asked to track a spot displayed in the laptop for calibrating the eye tracker and starting the experiment. Observers are instructed to limit their body movements in order to reduce undesired artifacts in the signals. The videos are presented in a balanced way to the observer to avoid order effects. Thus the positioning of each smiler's video, near the beginning/middle/end of the experiment, is different for each observer. Each video is followed by questions to identify the smile's real or posed nature, implying the smiler's affective state. For brevity of discussion, henceforth we will discuss e.g. 'real smile' as an affective state. Due to poor signal quality and unfinished data collection from two observers, the results are reported by analyzing data from twenty-four observers.

2.5 Signal Processing

Due to the nature of human bodies, physical movements and other effects, the recorded peripheral physiology is affected by noise like small signal fluctuations, eye blinking etc. To reduce this latter effect, eye blinking points are considered to be zero in pupillary responses. Then, cubic spline interpolation and 10-point Hann moving window average are employed to reconstruct and smooth the pupil data respectively [10]. This procedure is applied to the left and right eyes' pupillary response separately, and then averaged to find a single pupillary response signal for a specific observer. A low-pass Butterworth filter (order = 6, normalized cut-off frequency = 0.5) is used to smooth the GSR and BVP signals [11]. Then, maximum value normalization is applied to keep the signals in the range between 0 and 1.

2.6 Feature Extraction

The following six different time domain features are computed for each video related peripheral physiological signal. Let $X(n)$ represents the value of the nth sample of the processed peripheral physiological signals, $n = 1, 2, \ldots\ldots, N$.

1. Mean

$$\mu_x = 1/N \sum_{n=1}^{N} X(n) \tag{1}$$

2. Maximum

$$M_x = Max(X(n)) \tag{2}$$

3. Minimum

$$m_x = Min(X(n)) \tag{3}$$

4. Standard Deviations

$$\sigma_x = \sqrt{1/(N-1)\sum_{n=1}^{N}(X(n)-\mu_x)^2} \tag{4}$$

5. Means of the absolute values of the first differences

$$\delta_x = 1/(N-1)\sum_{n=1}^{N-1}|X(n+1)-X(n)| \tag{5}$$

6. Means of the absolute values of the second differences

$$\gamma_x = 1/(N-2)\sum_{n=1}^{N-2}|X(n+2)-X(n)| \tag{6}$$

These statistical features convey information such as typical range, gradient, and variation of the signals [19]. Then, we employed a feature level fusion (merge all features from BVP, GSR, and PR) technique before computing classification accuracies. In this case, there are 360 extracted features (20 videos $\times$ 6 features $\times$ 3 peripheral physiological signals) for an observer (half for posed smile videos and other half for real smile videos) and a total of 8,640 features for all 24 observers. We did not consider any features in the training set of a test observer that is related to that test observer. For example, suppose we consider the test data of observer 1 (O1) when watching the smiler 1, then the data of O1 while watching the other smilers' videos is not used to either train or test the classifier. Thus there are 18 (1 observer $\times$ 6 features $\times$ 1 smiler $\times$ 3 peripheral physiological signals) testing features and 7,986 (23 observers $\times$ 6 features $\times$ 19 smilers $\times$ 3 peripheral physiological signals) training features in each execution. Finally, average accuracies over all possible executions are reported. This leave-one-out process means that our classifiers have seen no physiological signals from training observers nor from training smilers in the test set, our results is thus completely independent.

3 Experimental Outcomes

Smilers' affective states are classified into two classes, namely real smiles and posed smiles from observers' peripheral physiological features. The analysis is executed on an Intel(R) Core™ i7-4790 CPU with 3.60 GHz, 16.00 GB of RAM, Operating System 64-bit computer using MATLAB R2014b. Three different types of classifier are used to compute classification performances, namely k-nearest neighbor (KNN), support vector machine (SVM), and neural network (NN). The feature sets are divided according to the test observer identifications, such as O1, O2 all the way to O24. When the test observer is O1, and other observers' (O2 to O24) features are used to train the classifiers, we call it O1 and so on. In a similar fashion, test smilers are identified by S1, S2 all the way to S20. According to our robust leave-one-out process, the final outcome of O1 is the average value over 20 executions (S1 to S20) for each physiological feature set.

Parameter tuning is found to be vital factor in determining classification accuracies using all three of these classifiers. We choose the default Euclidian distance metric for the KNN classifier and check the variation of classification accuracies with different K values. The results are depicted in Fig. 2, where error bars indicate standard deviations. It is clear from Fig. 2 that the classification accuracies decrease with increasing K. It is also seen that higher accuracies are found for even values of K compared to odd values of K. A similar result was found in the case of a Parkinson dataset [20], possibly this is due to some properties of human data in producing decision regions with unusual topologies.

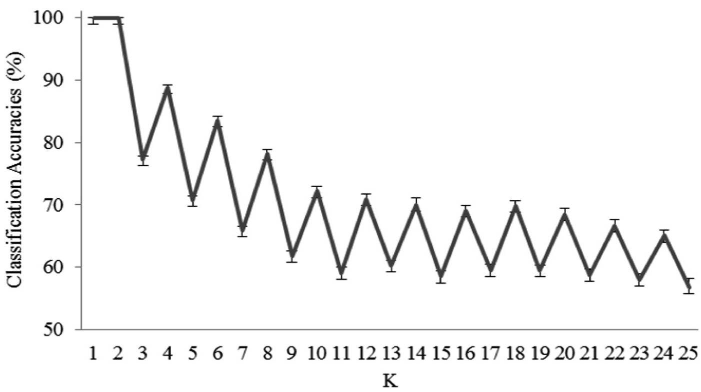

Fig. 2. Variation of accuracies for 'K' values of KNN, (Maximum value is 99.8%).

For SVM, the Gaussian radial basis kernel function is used with various scaling factors to compute classification accuracies. The variation of average accuracies with scaling factors is noticeable and explored in Fig. 3, where error bars indicate standard deviations. The classification accuracies gradually decrease with increasing scaling factors. The rate of decrease is higher for the low values of the scaling factor (from 1 to 5), and then this rate diminishes. Some research has focused on empirical analysis to find the best fitted scaling factors to report best performances from SVM classifier [21].

In NN, Levenberg-Marquardt training function with various numbers of hidden nodes are considered to compute classification accuracies. The variation of average classification accuracies with the various numbers of hidden nodes of NN classifier are shown in Fig. 4, again error bars indicate standard deviations.

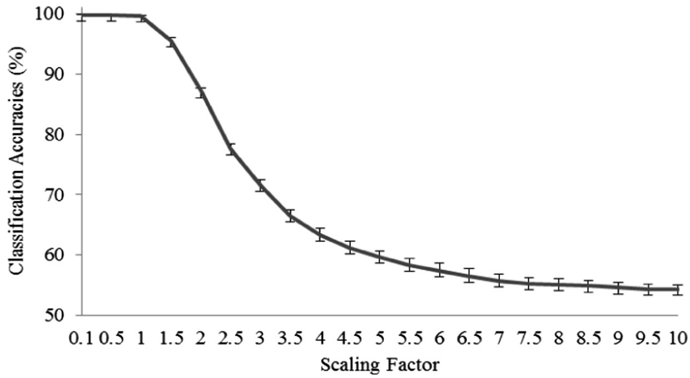

Fig. 3. Variation of accuracies to scaling factors of SVM, (Maximum value is 99.7%).

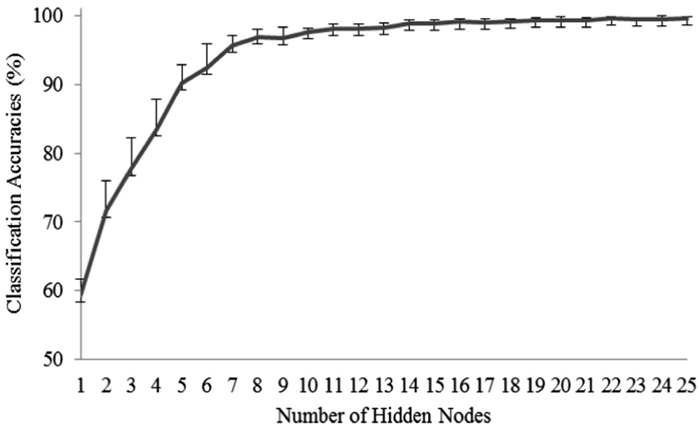

Fig. 4. Variation of accuracies to the no. of hidden nodes of NN, (Maximum value is 99.6%).

The average classification accuracies are improved with increasing number of hidden nodes as shown in Fig. 4. The errors are also seen to decrease with the increasing number of hidden nodes according to standard deviation computation. It has been necessary to focus on empirical analysis to find the best number of hidden nodes, as we expected and did find that the number of hidden nodes affects classification accuracies [22]. We note that our results are robust, yet the very high accuracies do require some discussion. We believe that the results are explained by results [23] showing highly conserved shared structure in neural activity across individuals in a consistent observation task. Our work in removing backgrounds, adjusting luminance and contrast, and order balancing of tasks has led to a consistent task. The results are also robust as they are leave-one-out of both subject and each test video.

4 Parameter Fusion

We investigate fusion of parameters using a simple ensemble over the decision of the above three classifiers (KNN, SVM, and NN) from the three techniques, in four ways. Firstly, we examine the effect of fusing the three best values, representing the situation where a thorough investigation of parameter values was done, to attempt to further improve the results. Secondly, we examine the most perverse setting where we use the worst results and fuse them, representing a very naïve user making particularly bad choices. Thirdly, we fuse midrange values, representing a naïve user who has expended some effort. Finally, we examine some combinations of best/midrange/worst results (see Table 1). We note that our robust leave-one-of-everything-out process is not able to overfit, as each observer-stimulus pair is used as a test set in different runs. This is admittedly a computationally expensive process for robustness.

It is noticeable from Figs. 2, 3, and 4 and Table 1 that the best classification accuracies are found for k = 1 (99.8%), s = 0.1 (99.7%), and n = 25 (99.6%) and the worst accuracies are found for k = 25 (56.7%), s = 10 (54.3%), and n = 1 (59.3%). For the midrange, we choose accuracies between 75–80%. Specifically, we choose k = 8 (78.2%), s = 2.5 (77.5%), and n = 3 (77.7%). Finally, we fuse the physiological features at different combinations of these parameter settings. We find that the ensemble classifier can improve the performance (highlighted in Table 1) for the worst results, and for combinations involving midrange results. We find that our feature level fusion does not improve the results when one or more of the best case results are included.

Table 1. Accuracies of ensemble classification with different combinations of parameters (where K, S, and N are the K values of KNN, scaling of SVM, and Nodes of NN)

	k	s	n	KNN	SVM	NN	Ensemble
All best	1	0.1	25	99.8	99.7	99.6	99.6
All worst	25	10	1	56.7	54.3	59.3	**73.7**
All mid	8	2.5	3	78.2	77.5	77.7	**87.6**
KNN best	1	10	1	99.8	54.3	59.3	87.1
KNN mid	8	10	1	78.2	54.3	59.3	**80.0**
KNN worst	25	0.1	25	56.7	99.7	99.6	94.6
SVM best	25	0.1	1	56.7	99.7	59.3	88.1
SVM mid	25	2.5	1	56.7	77.5	59.3	**80.1**
SVM worst	1	10	25	99.8	54.3	99.6	94.5
NN best	25	10	25	56.7	54.3	99.6	84.6
NN mid	25	10	3	56.7	54.3	77.7	**80.0**
NN worst	1	0.1	1	99.8	99.7	59.3	97.4

5 Conclusion

This paper investigates the effects of K values, scaling factors, and the number of hidden nodes, for KNN, SVM, and NN respectively, to distinguish between real and posed smiles from observers' peripheral physiological features while other factors remain unchanged. From the results of our robust leave-one-out process, we found substantial effects from the parameters we considered on the smile classification as real or posed, from observers' physiological features. We saw that lower K values and scaling factors, and higher number of hidden nodes were needed to find higher classification accuracies according to the architecture of each classifier. We noted that fusing results when we had optimized parameter values for each technique led to no improvement, strongly indicating that the errors made by each classifier must be quite similar. Fusing results from cases with less good parameter values led to improved classification results. We believe this would be a practical test for naïve users of these techniques to indicate that further parameter tuning should be done. In the future, we will consider other parameters of each classifier to check the variability of classification performance and to tune the parameters to design a robust system to distinguish between real and posed smiles in this context. We will also consider aggregation approaches designed for complex structured data such as physiological signals [24, 25], alternative artificial intelligence approaches [26–28], and the use of virtual or synthesised faces [29, 30].

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