An Independent Approach to Training Classifiers on Physiological Data: An Example Using Smiles

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Abstract. Training neural network and other classifiers on physiological signals has challenges beyond more traditional datasets, as the training data includes data points which are not independent. Most obviously, more than one sample can come from a particular human subject. Standard cross-validation as implemented in many AI tools gives artificially high results as the common human subject is not considered. This is handled by some papers in the literature, by using leave-one-subject-out cross-validation. We argue that this is not sufficient, and introduce our independent approach, which is leave-one-subject-and-one-stimulus-out cross-validation. We demonstrate our approach using KNN, SVM and NN classifiers and their ensemble, using an extended example of physiological recordings from subjects observing genuine versus posed smiles, which are the two kinds of the nicest smiles and hard for people to differentiate reliably. We use three physiological signals, 20 video stimuli and 24 observers/participants, achieving 96.1% correct results, in a truly robust fashion.

Keywords: Observers · Smilers · Physiological features
Independent approach · Affective computing

1 Introduction

Classification is an important task to classify new instances, and the use of 10 fold cross-validation is common. Particularly in the context of data from human measurements, leave-one-out cross validation is a useful technique for evaluating the performance of classification algorithms, which estimates out of sample predictive accuracy using within-sample fits. This technique is generally task dependent otherwise it may provide noisy outcomes [1] and/or inconsistent accuracies [2]. In this paper, first we introduce our example domain with background and then our *Independent Approach* in Sect. 3.

In this example domain, we choose observers' physiological responses while watching real and posed smile videos. As in practical situation, life provides many reasons to smile that generally indicate pleasure, appreciation, happiness, or satisfaction. A smile face evokes positive feelings and conveys different messages to others. Because people can smile in different situations either positive or negative, such as a polite smile, false smile, acted smile, or smile to hide something [3]. We mean the later

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types of smiles as posed smiles and smile that signifies happiness as real/genuine smiles. The correct reading of smilers' faces seems to guarantee the understanding of smiler's affective states appropriately. In this connection, the potential application of this system are not limited to the finding the relationship between smilers' facial changes with the observers' physiology, but also this system can be applied to design sensing technologies from care-givers' peripheral physiology to understand patients' mental states, detecting avatars' emotional realism, and so on. Even the performance of face recognition systems can be improved when trained by smiling faces [4].

In the past, researchers focused on analyzing smilers' faces directly to differentiate between real and posed smiles. Dibeklioğlu et al. [6] implemented their own computer vision technique on the smilers' facial features. Hoque et al. [7] used similar features to discriminate between delighted and frustrated smiles. Gan et al. [8] applied two-layer deep Boltzmann machine on smiler's images. Gunadi et al. [9] used linear support vector machine to detect fake smiles from smiler's faces. Cohn et al. [10] measured the timing of face motion during smiles on images. Frank et al. [5] and Hoque et al. [7] considered observers' verbal responses to recognize real smiles. It is usually very hard to discriminate real and posed smiles by relying on observers' verbal responses [5], even though people generally emotionally react to others' emotion during face to face interaction [11]. This is because the smile is one of the easiest facial expressions that can be faked voluntarily [6]. But observer's peripheral physiology is associated with emotional states [11] and can be used in classifying smiler's affective state. In general, this concept can be applicable in security systems. For example, suspect can smile during verifying their truthfulness in a hearing, interrogation, or customs. Then we may apply this concept to identify the genuineness of a smile from lawyers, police, or custom officers' peripheral physiology.

Understanding a smiler's affective conditions can be achieved from observers' physiological states. This is because smilers show their smile using facial expressions, and observers will have certain impressions or feelings caused by the smiler facial actions, which makes a change to the observers' peripheral physiology. The physiological signals are not voluntarily controllable and have the ability to vary differently in different circumstances [12]. Thus, physiological signals [13–15] are considered in several studies to be useful to understand facial expressions. Here, we considered three of these signals to discriminate between real and posed smiles, namely blood volume pulse (BVP), galvanic skin response (GSR), and pupillary response (PR).

The pupillary responses can change for many reasons, including memory load, stress, pain, watching videos, face to face interactions etc., and would offer a good method for classifying real and posed real smiles, because it does not require to attach any sensors either to the observer or to the smiler [13]. GSR is an automatic reaction that causes continuous electrical changes in sweat gland activity of human skin and is considered one of the strongest signals in emotion detection [14]. BVP is another physiological signal that uses infrared light to measure blood volume changes in arteries of the human body and the shape of BVP reflects the emotional changes of the human [15]. Due to the involuntary nature of the physiological signals, and observers lower verbal response rate for classifying real and posed smiles, we considered observers' physiology here. It is also worth mentioning that smiles are chosen due to the universal role in presenting emotion of happiness for the smiler and in being understood as signs that observers note as sociality or closeness. In the end, we extract six temporal features from each of the above physiological signals and measure classification performances by leave-one-out-cross validation techniques.

In this connection, the motivation of this research comes from the usefulness of the Assistive Context Aware Toolkit (ACAT), which was designed for Hawking to enable him to control his computer and communicate with others [22]. We are hoping to design similar technologies as Professor Hawking's from the care-givers' peripheral physiology in future, and we choose smiles at the first instance. In previous research, people considered a leave-one-out approach because they were using either smilers' facial expression [6, 16] or observers' verbal responses [7]. But none of them analyzed observers' (such as care givers) physiological responses to recognize smilers' facial expressions. In this context, leave-one-observer-out or leave-one-smiler-out approach is not fully noise free or robust, because when leave-one-observer-out approach is used then the training data is contaminated by the smilers' information, and vice versa. Thus, our work initiates a new approach called an Independent Approach that highlights the main idea of noise free test data by removing potentially contaminating data from the training data.

2 Smiles and Observers' Physiology

This section addresses the example data (physiological signal) collection and the processing procedures. This is the initialization section before using our Independent Approach, as well as input data preparation section for our classifiers.

2.1 Smilers

Twenty smilers' videos were randomly collected from four databases (five from each), namely UvA-NEMO [16], MAHNOB [17], MMI [18], and CK+ [19]. MAHNOB and NEMO databases were chosen to collect real smiles, because participants' smiles were elicited in these databases by showing a number of pleasant or funny video clips. CK+ and MMI databases were considered to collect posed smiles, because participants were asked instructed or requested to show a smile in these databases. MATLAB platform was considered to process the collected smile videos. The height, width, format, color, and duration of each smile video were processed into 336 pixels, 448 pixels, mp4, grey, and 5 s respectively. Due to smile time duration being 0.5 s to 4 s in general [3], we choose smiler' video length up to 5 s long that was adjusted by controlling the frame rate of videos. To avoid the effect of light/dark backgrounds, smilers' faces were masked before showing them to the observers. Finally, the MATLAB SHINE toolbox [20] were used to adjust the luminance (128 ALU (Arbitrary Linear Unit)) and contrast (32 ALU) of each smile videos.

2.2 Observers

Twenty-six (11 female, 15 male) right-handed participants participated voluntarily in this experiment (age: 30.7 ± 5.96 (mean ± Std.)). They signed written consent forms before starting the experiment. The experiment was approved by the Australian National University's Human Research Ethics Committee.

2.3 Data Recording

Smile videos were presented to the observers using an ASUS laptop, and observers were seated in front of the laptop comfortably, in a static chair before starting the experiment. Each smile video was followed by a question: How did this smile look to you? Happy (Real/Spontaneous/Genuine) or Fake (Posed/Acted). Observers used a computer mouse to input their answers. Three physiological signals, being pupillary responses, BVP, and GSR were recorded at a sampling rate of 60 Hz, 64 Hz, and 4 Hz respectively, according to the device specifications. The pupillary responses were recorded using The Eye Tribe (theeyetribe.com) remote eye-tracker system, and BVP and GSR were recorded using the Empatica E4 (www.empatica.com). Before starting the experiment, the eye tracker was calibrated and observers were requested to limit their body movements to minimize the noise in the signals. The smile videos were presented to the observers in an order balanced way. It is worth noting that the results are reported in this paper by analyzing twenty-four observers' data due to very noisy physiological responses from the other two observers.

2.4 Signal Processing

To reduce the undesired noise from the peripheral physiological signals, eye blink points (which show up as zero in pupillary responses) were reconstructed using interpolation technique (cubic spline), and pupil data were smoothed using moving average filtering (Hanning window) [11]. Butterworth filter (low-pass, order = 6) was considered to filter out the noises from BVP and GSR signals [12]. To reduce between-observer differences, the maximum value normalization technique was applied to keep the signals and their extracted features in the range between 0 and 1. In this sense, each value of a particular observer's specific physiological signal is divided by the maximum value of that observer's specified physiological signal [19]. Before normalizing, signals were kept over the positive axis by changing their dc label.

2.5 Signal Extraction

Six temporal features are calculated from each physiological signal relevant to each smile video for an observer. These features convey the information of observers' physiological behaviours as well as their thinking to the smilers' affective states as typical range, variation and gradient like characteristics [21]. In this specific case, we extracted 120 features (20 smile videos $\times$ 6 features) from an observer (50% from real smiles and the rest from posed smiles) and 2880 features in total (120 features $\times$ 24 observers) for all observers, considering each signal (BVP or GSR or PR). Let $y(n)$ represents the value of the nth sample of the processed physiological signals $n = 1, \ldots\ldots\ldots N$.

1. Means

$$\mu_y = 1/N \sum_{n=1}^{N} y(n) \tag{1}$$

2. Maximum

$$M_y = \max(y(n)) \tag{2}$$

3. Minimum

$$m_y = \min(y(n)) \tag{3}$$

4. Standard Deviations

$$\widetilde{\sigma}_y = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} \left(y(n) - \mu_y\right)^2} \tag{4}$$

5. Means of the absolute values of the first differences

$$\widetilde{\delta}_y = \frac{1}{N-1} \sum_{n=1}^{N-1} |\widetilde{y}(n+1) - y(n)| \tag{5}$$

6. Means of the absolute values of the second differences

$$\widetilde{\gamma}_y = \frac{1}{N-2} \sum_{n=1}^{N-2} |\widetilde{y}(n+2) - y(n)| \tag{6}$$

3 An Independent Approach

We propose a novel approach we call an *independent approach*. This is independent in the sense that the test data is fully free from training data: for each test where observer '*Om*' watches the video of smiler '*Sn*', the classifier is not contaminated by those observers' physiological features and it is not contaminated by other observers' physiological features while watching that smiler. So, beyond the normal leave-one-observer-out cross-validation, we are also performing leave-one-smiler-observer-out at the same time. We consider this fully independent approach to be necessary to validly conclude than a classifier is not contaminated during training. This level of rigor is not matched in the literature. For example, suppose observer 1 (*O1*) (when watching the n^{th} smiler (*Sn*)) is considered as test data, then any other data related to *O1* is not used to either train or test the classifier as illustrated in Fig. 1.

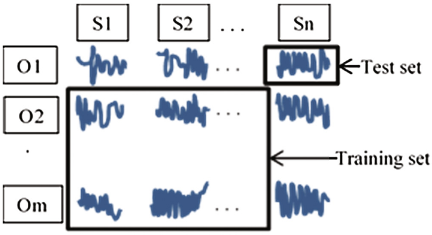


Fig. 1. An independent approach to compute classification accuracies, S = Smiler, O = Observer, n = 20, and m = 24. One of 437 (i.e. 19 × 23) training + test sets shown.

In total, there are n × m sets of physiological data, for each of n Smilers, being watched by m Observers, i.e. 480 in this case. A smiler independent (leave-one-video-out) process would train using n − 1 Smiler videos from m Observers, and test using the n^{th} video, repeatedly, so this 19 × 24 size of training data would be repeated 20 times. An observer independent (leave-one-observer-out) process would train using n Smiler videos from m − 1 Observers, and test using the m^{th} observer, repeatedly, so the 20 × 23 size of training data would be repeated 24 times. In our fully Independent Approach, we train using n − 1 Smiler videos from m − 1 Observers, and test using the n^{th} video from the m^{th} observer, repeatedly, so the 19 × 23 size of training data is repeated 480 times. Finally, average classification accuracies are reported from all these executions.

An advantage of this approach is that it is quite computationally intensive; it is as robust as possible. It also ensures the quality of training data by removing redundant and irrelevant data, which is not possible in the other two approaches, because they are not fully independent as discussed in previous paragraphs. In the case of leave-one-observer-out approach, trained data is contaminated by smilers, and vice versa in case of leave-one-smiler-out approach.

4 Results and Discussion

The observed smiles are classified into real smile and posed smile. The classification accuracies are computed using k-nearest neighbour (KNN), support vector machine (SVM), neural network (NN), and ensemble over the decision of these three classifiers. We considered default parameter settings in MATLAB as Euclidean distance matric and 5 nearest neighbours for KNN, sequential minimal optimization method and Gaussian radial basis kernel function with scaling factor of 1 for SVM, Levenberg-Marquardt training function with 10 hidden nodes for NN classifiers respectively. The mean square error performance function is considered to compute classification accuracies from each classifier.

The features are divided according to the test smiler identifications, such as S1, S2 all the way to S20. When test smiler is S1 and other smilers' (S2 to S20) data is used to train the classifiers, we call it S1 and so on. In a similar fashion, test observers are identified by O1, O2 all the way to O24. According to the independent approach, the final outcome of O1 is the average value over 20 executions (S1 to S20) for each set of physiological features. The outcomes from observer's PR features are explored in Table 1.

Table 1. Individual classification accuracies (%) of 24 observers

	KNN	SVM	NN	Ensemble		KNN	SVM	NN	Ensemble
O1	69.6	72.1	77.6	83.2	**O13**	68.0	73.3	78.1	84.8
O2	67.6	72.4	69.4	83.2	**O14**	69.2	72.6	70.5	84.3
O3	69.4	71.2	75.1	84.1	**O15**	69.0	71.5	82.9	84.9
O4	69.0	73.1	76.3	85.1	**O16**	69.2	72.1	82.0	84.7
O5	68.7	71.2	74.7	82.9	**O17**	69.0	74.0	82.9	85.3
O6	69.2	71.7	73.7	83.5	**O18**	69.9	70.5	75.6	84.1
O7	68.5	71.5	76.3	83.6	**O19**	68.7	71.9	68.3	83.7
O8	69.2	71.7	79.0	83.8	**O20**	69.4	71.9	73.3	83.7
O9	69.0	71.9	72.8	84.0	**O21**	69.9	71.5	80.1	85.0
O10	69.0	71.7	76.5	**82.5**	**O22**	68.3	71.0	77.9	84.4
O11	70.3	70.3	71.9	83.3	**O23**	69.6	71.5	79.0	85.0
O12	70.3	71.0	76.3	84.4	**O24**	70.3	72.4	79.7	**85.6**

It is obvious from Table 1 that the ensemble classifier shows higher classification accuracies compared to the other classifiers. The classification accuracies are quite similar for each observer at discriminating between posed and real smiles, with highest value of 85.6% for O24 and lowest of 82.5% for O10. Table 1 depicts the results from PR features. The variation of the outcomes changes in a similar fashion, when training and testing with GSR or BVP features. The comparative results of GSR, BVP and PR features from the ensemble classifier using our independent approach are shown in Table 2.

Table 2. Ensemble classification results for 24 observers (individual)

	GSR	BVP	PR		GSR	BVP	PR
O1	84.5	83.5	83.2	**O13**	84.9	84.1	84.8
O2	83.0	84.6	83.2	**O14**	84.1	83.7	84.3
O3	85.8	85.1	84.1	**O15**	83.5	84.5	84.9
O4	84.5	84.9	85.1	**O16**	83.3	84.1	84.7
O5	84.3	83.2	82.9	**O17**	84.5	85.2	85.3
O6	84.2	84.0	83.5	**O18**	85.0	82.7	84.1
O7	83.2	85.3	83.6	**O19**	83.4	84.1	83.7
O8	85.2	**85.9**	83.8	**O20**	82.7	83.3	83.7
O9	82.7	85.1	84.0	**O21**	**85.2**	84.4	85.0
O10	83.8	85.0	**82.5**	**O22**	84.0	83.4	84.4
O11	84.3	85.4	83.3	**O23**	**81.1**	84.1	85.0
O12	83.1	**82.5**	84.4	**O24**	85.0	84.2	**85.6**

There are no large differences among observers' peripheral physiological features to discriminate between posed and real smiles as shown in Table 2. In comparison, GSR shows the highest classification accuracy of 85.2% for O21, BVP shows 85.9% for O8 and PR shows 85.6% for O24 respectively, where the lowest accuracies of 81.1% for O23, 82.5% for O12, and 82.5% for O10 are found in the case of GSR, BVP, and PR features respectively. The average accuracies over all observers are shown in Fig. 2. Standard deviations are represented by error bars.

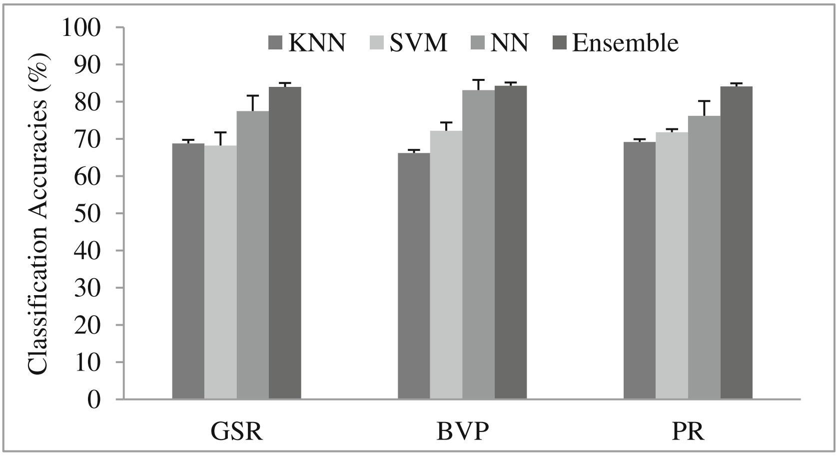
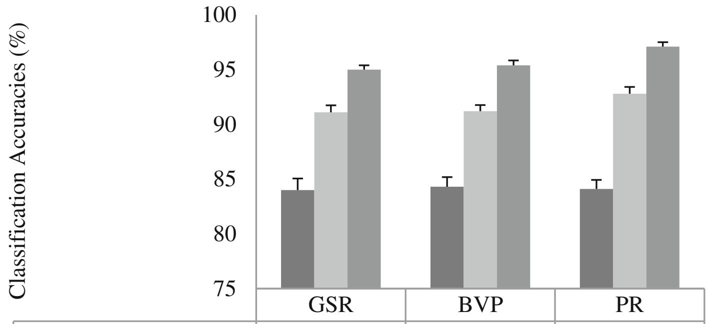


Fig. 2. Average classification accuracies using independent approach.

It can be seen from Fig. 2 that higher accuracies are reported for the ensemble classifier, and then for NN, SVM, and KNN classifiers respectively. We also test another two possible approaches, namely leave-one-smiler-out (means that the classifiers have seen no physiological features from any observers on that smiler, i.e. results are smiler independent) and leave-one-observer-out (that means the classifiers have not seen any physiological features from any smilers of that observer, i.e. results are observer independent). The results of three approaches using the ensemble classifier are explored in Fig. 3 where standard deviations are denoted by error bars.

It can be seen from Fig. 3 that higher accuracies of 97.1% is found from PR features using the observer independent approach. Although we leave out the data of the test observer from training, there was information of similar smilers' videos that were observed by the other observers. In the case of the smiler independent approach, higher accuracy of 92.8% is found from PR features where the information of similar observers were seen to the training data, although data of smilers' videos were not considered to test the classifiers. On the other hand, our independent approach shows a bit lower accuracy of 84.1% compared to the other two approaches. It is expected that other two approaches show higher accuracies compared to ours, because they use test data relevant information during training, but it does not occur in our case. Thus our Independent Approach is robustly applicable in various situations, such as verifying trustworthiness from judge's physiological signal, making decision of patients from care-givers' physiology, and so on; specially who wish to make decision from observers' physiology.



	GSR	BVP	PR
Independent Approach	84	84.3	84.1
Smiler Independent	91.1	91.2	92.8
Observer Independent	95	95.4	97.1

Fig. 3. Average classification accuracies from ensemble classifier.

To improve the classification accuracies, using our Independent Approach, in discriminating between posed and real smiles from observers' physiological features, a feature level fusion (concatenating all features from PR, GSR, and BVP) technique is employed. It does improve the average classification accuracy to 96.1% (±0.25) with the ensemble classifier. The same information fusion approach has much less benefit on the less robust observer-independent (97.2% ± 0.49) and smiler-independent (93.7% ± 0.82) approaches. The lower smiler-independent result implies there is more information in the smilers than in the observers, further suggesting that the observer-independent approach is contaminated with this extra information. Our independent approach achieves 96.1% without this contamination.

On the other hand, observers were averagely 59.0% (±11.13) correct according in their verbal responses. A final accuracy of 96.1% from our Independent Approach demonstrated that observers' automatic physiological responses are strong indicators to discriminate between posed and real smiles with a significant degree of accuracy. In comparison, Dibeklioğlu et al. [6], Hoque et al. [7], Gan et al. [8], and Cohn et al. [10] used leave-one-subject-out approach and reported 89.84%, 92.30%, 91.73%, and 93.0% correctness respectively. It is also worth noting that they used the approach on the features that were extracted from smilers' facial expressions, but we extracted features from observers' physiology while watching the smilers' video. Thus our system is more robust and effective in this specific or similar type of cases.

5 Conclusion

We have overcome the effect of biasing on testing set from training physiological features using an independent approach and showed that high accuracy results are achievable using a highly robust cross-validation approach. We considered four classifiers to discriminate between posed and real smiles from observers' physiological features using this independent approach. The ensemble classifier performs better than other classifiers. It provides accuracies of about 84% from individual physiological features (PR, BVP, or GSR), where two other approaches, called smiler independent and observer independent, show higher accuracies compared to independent approach. Feature level fusion improves the classification accuracy of 96.1% using a simple ensemble technique. In this context, we perform the analysis on observers' physiological features without hassling smilers and can perform this analysis on historical data. The final accuracy figure obtained from observers' fused physiological features to distinguish smilers' affective states into real or posed, shows that this system could be applicable in many situations, such as patients' mental state monitoring, verifying trustworthiness during questioning, relationship management, and so on. This is in agreement with the physiological features of observers in affective computing area indicating that smilers leak their intentions through their facial behaviors.

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