Detection of Genuine and Posed Facial Expressions of Emotion: A Review

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Abstract
Facial expressions of emotion play an important role in human social interactions. However, posed acting is not always the same as genuine feeling. Therefore, the credibility assessment of facial expressions, namely, the discrimination of genuine (spontaneous) expressions from posed (deliberate/volitional/deceptive) ones, is a crucial yet challenging task in facial expression understanding. Rapid progress has been made in recent years for automatic detection of genuine and posed facial expressions. This paper presents a general review of the relevant research, including several spontaneous vs. posed (SVP) facial expression databases and various computer vision based detection methods. In addition, a variety of factors that will influence the performance of SVP detection methods are discussed along with open issues and technical challenges.

Keywords
Posed vs. Spontaneous, facial expression of emotion, expression classification

Introduction
Facial expressions, one of the main channels for understanding and interpreting emotions among social interactions, have been studied extensively in the past decades (Motley and Camden 1988; Zuckerman et al. 1976). Most existing research works have focused on automatic facial expression recognition based on Ekman’s theories (Ekman and Keltner 1997), which suggests six basic emotions universal in all cultures, including happiness, surprise, anger, sadness, fear, and disgust. However, are facial expressions always the mirror of our innermost emotions as we have believed for centuries? Recent research (Crivelli et al. 2015) has found that facial expressions do not always reflect our true feelings. Instead of reliable readouts of people’s emotional states, facial expressions tend to be increasingly posed and even deliberately to show our intentions and social goals. Therefore, understanding the credibility of facial expressions in revealing emotions has become an important yet challenging task in human behavioral research especially among the studies of social interaction, communication, anthropology, personality, and child development (Bartlett et al. 1999).

In the early years, research of discriminating genuine facial expressions from posed ones heavily relied on a variety of observer-based systems (Mehu et al. 2012). Rapid advances in computer vision and pattern recognition especially deep learning techniques have recently opened up new opportunities for automatic and efficient separation of genuine facial expressions from posed ones. A variety of SVP facial expression detection methods (Valstar et al. 2006; Dibeklioglu et al. 2010; Wu et al. 2014; Huynh and Kim 2017; Park et al. 2020), as well as publicly available databases (Wang et al. 2010; Mavadati et al. 2016; Cheng et al. 2018; Pfister et al. 2011), have been proposed for facial expression credibility analysis.

As of today, there has been no systematic survey yet to summarize the advances of SVP facial expression detection in the past two decades. To fill in this gap, we present a general review of the pioneering works as well as most recent studies in this field including both existing SVP databases and automatic detection algorithms. Through literature survey and analysis, we have organized existing SVP detection methods into four categories (action units, spatial patterns, visual features, and hybrid) and identified a number of factors that will influence the performance of SVP detection methods. Furthermore, we attempt to provide some new insights into the remaining challenges and open issues to address in the future.

Spontaneous vs. posed facial expression databases
Early studies on facial expressions are mostly based on posed expressions due to the easier collection process, where the subjects are asked to display or imitate each basic emotional expression. Spontaneous facial expressions, however, as natural expressions, need to be induced by various stimuli, such as odours (Simons et al. 2003), photos (Gajšek et al. 2009), and video clips (Pfister et al. 2011; Petridis et al. 2013). There have been several databases with single or...
multiple facial expressions collected to promote the research in automatic facial expression credibility detection. This section focuses on databases with both spontaneous and posed facial expressions, and provides the details of existing public databases (see an overview in Table 1).

The MMI facial expression database (Pantic et al. 2005) was first collected with only posed expressions for facial expression recognition. Later data with three spontaneous expressions (disgust, happiness, and surprise) were added with audio-visual recordings based on video clips as stimulus (Valstar and Pantic 2010). USTC-NVIE (Wang et al. 2010) is a visible and infrared thermal SVM database. Six spontaneous emotions consisting of image sequences from onset to apex∗, were also induced by screening carefully selected videos, while the posed emotions consist of apex images. CK+ database (Lucey et al. 2010), UvA-NEMO (Dibeklio˘glu et al. 2012), and MAHNOB database (Petridis et al. 2013) all focused on the smile, which is the easiest emotional facial expression to pose voluntarily. Specifically, the video sequences in CK+ database were fully coded based on Facial Action Coding System (FACS) (Ekman 1997) for facial action units (AUs) as emotion labels, while videos in MAHNOB recorded both smiles and laughter with microphones, visible and thermal cameras.

SPOS Corpus (Pfister et al. 2011) included six basic SVP emotions, with labels for onset, apex, offset and end by two annotators according to subjects’ self-reported emotions. BioVid dataset (Walter et al. 2013) specifically targeted pain with heat stimulation, and both biosignals (such as SCL, ECG, EMG, and EEG) and video signals were recorded. DISFA and DISFA+ database (Mavadati et al. 2013, 2016) contain spontaneous and posed facial expressions respectively, with 12 coded AUs labels by FACS and 66 landmark points. In addition to basic facial expressions, DISFA+ also includes 30 facial actions by asking participants to imitate and pose the specific action. Proposed for ChaLearn LAP Real Versus Fake Expressed Emotion Challenge in 2017, the SASE-FE database (Wan et al. 2017; Kulkarni et al. 2018) collected 6 expressions by asking participants to pose artificial facial expressions or showing participants video clips to induce genuine ones. Figure 1 illustrates several examples of video clips selected by psychologists to induce specific emotions in this database.

Most recently, a large scale 4D database, 4DFAB (Cheng et al. 2018), was introduced with 6 basic SVP expressions, recorded in four different sessions spanning over a five-year period. This is the first work to investigate on the use of 4D spontaneous behaviours in biometric applications.

Detection of genuine and posed facial expressions

Posed facial expressions, due to the deliberate and artificial nature, always differ from genuine ones remarkably in terms of intensity, configuration, and duration, which have been explored as distinct features for SVP facial expression recognition. Based on different distinct clues, we classify existing methods into four categories: muscle movement (action units) based, spatial patterns based, visual features based, and hybrid methods.

Muscle movement (action units) based

Early research on distinguishing genuine facial expressions from posed ones rely a lot on the analysis of facial muscle movement. This class of methods are based on the assumption that some specific facial muscles are particularly trustworthy cues due to the intrinsic difficulty of producing them voluntarily (Ekman 2003). In these studies, the Facial Action Coding System (FACS) (Ekman and Rosenberg 2005) is the most widely-used tool for decomposing facial expressions into individual components of muscle movements, called Action Units (AUs), as shown in Figure 2(a). Several studies have explored the differences of muscle movements (AUs) in spontaneous and posed facial expressions, including the AUs amplitude, maximum speed, and duration (please refer to Figure 2(b) for an example).

It is known that spontaneous smiles have a smaller amplitude, but a larger and more consistent relation between amplitude and duration than deliberate smiles. Based on this observation, method in (Cohn and Schmidt 2003) used timing and amplitude measures of smile onsets for detection and achieved a 93% recognition rate with a linear discriminant analysis classifier (LDA). The method in (Valstar et al. 2006) was the first attempt to automatically determine whether an observed facial action was displayed deliberately or spontaneously. They proposed to detect SVP brow actions based on automatic detection of three AUs (AU1, AU2, and AU4) and their temporal segments (onset, apex, offset) produced by movements of the eyebrows. Experiments on combined databases achieved 98.80% accuracy. Later works (Bartlett et al. 2006, 2008) extracted five statistic features (median, maximum, range, first to third quartile difference) of 20 AUs in each video segment for classification of posed and spontaneous pain. They reported a 72% classification accuracy on their own dataset. To detect SVP smile, method in (Schmidt et al. 2009) quantified lip corner and eyebrow movement during periods of visible smiles and eyebrow raises, and found maximum speed and amplitude were greater and duration shorter in deliberate compared to spontaneous eyebrow raises. Aiming at multiple facial expressions, the method (Saxen et al. 2017) generated a 440-dimensional statistic feature space from the intensity series of 7 facial AUs, and increased the performance to 73% by training an ensemble of Rank SVMs on SASE-FE database. Differently, recent work in (Racoviteanu et al. 2019) used AlexNet CNN architecture on 12 AU intensities to obtain the features in transfer learning task. Training on DISFA database, and testing on SPOS, the method achieved an average accuracy of 72.10%. A brief overview of these methods has been shown in Table 2.

*Onset, apex, along with offset, and neutral, are four possible temporal segments of facial actions during the expression development (generally in the order of neutral→onset→apex→offset→neutral). In the onset phase, muscles are contracting and changes in appearance are growing stronger. In the apex phase, the facial action is at a peak with no more changes in appearance. The offset phase describes that the muscles of the facial action are relaxing and the face returns to its original and neutral appearance, where there are no signs of activation of the investigated facial action.
Table 1. Description of SVP facial expression databases

| Dataset    | Expression | #Sub | #M/F | Age       | #P/S | Format          | Feature                                                                 | Reference           |
|------------|------------|------|------|-----------|------|-----------------|-------------------------------------------------------------------------|---------------------|
| MMI        | Multiple   | 25   | 13/12| 20-32     | 2489/392 | Video           | Audio-visual; single and combinations of AUs                             | Valstar and Pantic (2010) |
| USTC-NVIE  | Multiple   | 215  | 157/58| 17-31     | -/-   | Frame           | Visible + infrared thermal images                                      | Wang et al. (2010)   |
| CK+        | Smile      | 210  | 65/145| 18-50     | 593/122 | Frame           | Multiple posed expressions, only un-posed smile, FACS coded             | Lucey et al. (2010)  |
| SPOS Corpus| Multiple   | 7    | 4/3   | /         | 51/147 | Frame           | Visible + infrared                                                     | Pfister et al. (2011) |
| UvA-NEMO   | Smile      | 400  | 215/185| 8-76      | 643/597 | Video           | The largest smile database                                              | Dibeklioğlu et al. (2012) |
| MAHNOB     | Smile      | 22   | 12/10 | ∼28       | 563/101 | Video           | Audio-visual, thermal recording                                        | Petrissis et al. (2013) |
| BioVid     | Pain       | 90   | 45/45| 18-65     | 630/8700 | Video           | Biopotential signals, depth information                                | Walter et al. (2013) |
| DISFA      | Multiple   | 27   | 15/12| 18-50     | 0/54  | Video           | AU labels and landmarks                                                | Mavadati et al. (2013) |
| DISFA+     | Multiple   | 9    | 4/5   | 18-50     | 644/0  | Frame           | AU labels, 42 facial actions                                           | Mavadati et al. (2016) |
| SASE-FE    | Multiple   | 50   | -/-   | 19-36     | 300/300 | Video           | 3 subsets                                                               | Wan et al. (2017)    |
| 4DFAB      | Multiple   | 180  | 120/60| 5-75      | -/-   | 4D video        | Dynamic high-resolution 3D faces, 79 face landmarks                     | Cheng et al. (2018)  |

Figure 1. Examples of video clips to induce specific emotions in SASE-FE database (Copyright permission is obtained from Kulkarni et al. (2018)).

Figure 2. Examples of FACS AUs, (a) Upper and lower face AUs (Copyright permission is obtained from la Torre De, F et al. (2015)), (b) Different AUs in Duchenne smiles (AU 6, 12, 25) and non-Duchenne smiles (AU12, 25) (Copyright permission is obtained from Bogodistov et al. (2017)).

**Spatial patterns based**

This category of methods aim at exploring spatial patterns based on temporal dynamics of different modalities such as facial landmarks and shapes of facial components. A multimodal system based on fusion of temporal attributes including tracked points of face, head and shoulder was proposed in (Valstar et al. 2007) to discern posed from spontaneous smiles. Best results were obtained with late fusion of all modalities of 94% on 202 videos from MMI database. Specifically regarding smile, a study in (Van Der Geld et al. 2008) analyzed differences in tooth display, lip-line height, and smile width between SVP smiles. They revealed several findings in SVP smiling differences. For example, maxillary lip-line heights in genuine smiles were...
temperature information from thermal images, and extracted based on infrared images, (Liu and Wang 2012) used facial detection performance of 80.0% on the SPOS database. Also, Learning (MKL) classifier, which achieved outstanding fused the NIR and VIS modalities with Multiple Kernel patterns from Three Orthogonal Planes (CLBP-TOP), and proposed a new feature, named Completed local binary UvA-NEMO dataset. Another method (Pfister et al. 2011) stage. The two-stage system achieved 88% accuracy on the facial actions using Gabor features and a SVM classification from real pain. It consisted of a detection stage for 20 Visual features (appearance) based such as (Littlewort et al. 1997) with parametric bias to extract features in the spatial-temporal domain from extracted facial landmarks, and achieved 66% accuracy on the BABE-FE database. Table 3 presents an overview of these spatial pattern based detection methods.

### Visual features based
Visual features (appearance) based such as (Littlewort et al. 2009) designed a two-stage system to distinguish faked pain from real pain. It consisted of a detection stage for 20 facial actions using Gabor features and a SVM classification stage. The two-stage system achieved 88% accuracy on the UvA-NEMO dataset. Another method (Plisfer et al. 2011) proposed a new feature, named Completed local binary patterns from Three Orthogonal Planes (CLBP-TOP), and fused the NIR and VIS modalities with Multiple Kernel Learning (MKL) classifier, which achieved outstanding detection performance of 80.0% on the SPOS database. Also based on infrared images, (Liu and Wang 2012) used facial temperature information from thermal images, and extracted statistical features from five facial subregions for SVP facial expression detection. Finally, the approach in (Gan et al. 2015) proposed to use pixel-wise difference between onset and apex face images as input features of a two-layer deep Boltzmann machine to distinguish SVP expressions. They achieved 84.62% and 91.73% on the SPOS and USTC-NVIE databases respectively.

More recently, Mandal et al. (2016) explored several features, including deep CNN features, local phase quantization (LPQ), dense optical flow and histogram of gradient (HOG), to classify SVP smiles. With Eulerian Video Magnification (EVM) for micro-expression smile amplification, the HOG features outperformed other features with an accuracy of 78.14% on UvA-NEMO Smile Database. Instead of using pixel-level differences, the method (Xu et al. 2017) designed a new layer named comparison layer for deep CNN to generate high-level representations of the differences of onset and apex images, and verified its effectiveness on SPOS (83.34%) and USTC-NVIE database (97.98%). The latest work Tavakolian et al. (2019) present a Residual Generative Adversarial Network (R-GAN) based method to discriminate SVP pain expression by magnifying the subtle changes in faces. Experiment results have shown the state-of-the-art performance on three databases, with 91.34% on UNBC-McMaster (Lucy et al. 2011) with spontaneous pain expressions only, 85.05% on BiodVid, and 96.52% on STOIC (Roy et al. 2007) with posed expressions only. A brief overview of these methods has been shown in Table 4.

### Hybrid methods
Hybrid methods combined different classes of features for discriminating SVP facial expressions. Experiments on still images were conducted in (Zhang et al. 2011) to show that appearance features (e.g., Scale-Invariant Feature Transform (SIFT) Lowe (2004)) play a significantly more important role than geometric features (e.g., facial animation parameters (FAP) Aleksic and Katsaggelos (2006)) on discriminating genuine and posed facial expressions. Similarly, (Huynh and Kim 2017) used mirror neuron modeling and Long-short Term Memory (LSTM) Hochreiter and Schmidhuber (1997) with parametric bias to extract features in the spatial-temporal domain from extracted facial landmarks, and achieved 66% accuracy on the BABE-FE database. Table 3 presents an overview of these spatial pattern based detection methods.

| Reference            | Method (features)                                                   | Expression       | AU         | Classification | Database      | Accuracy  |
|----------------------|---------------------------------------------------------------------|------------------|------------|----------------|---------------|-----------|
| Cohn and Schmidt (2003) | Using timing and amplitude measures of smile onsets                | Smile            | 6, 12, 15, 17 | LDA            | Self-collected | 93.00%    |
| Valstar et al. (2006)  | Temporal dynamics of brow actions based on AUs and their temporal segments (onset, apex, offset) | Multiple (6)     | 1, 2, 4     | Relevance Vector Machine | MM1+DS118+ CK*262 | 90.80%    |
| Bartlett et al. (2008) | Statistic features of 20 AUs in each video segment                  | Pain             | 1, 2, 4-7, 9, 10, 12, 14, 15, 17, 18, 20, 23-26 | Nonlinear SVM | Self-collected | 72.00%    |
| Schmidt et al. (2009)  | Maximum speed and amplitude of movement onset of lip corner and eyebrow; AFINA to measure movement | Smile            | 6, 12, 14, 15, 17, 23, 24, 50 | /              | /             | /         |
| Saxen et al. (2017)    | from the intensity time series of 7 facial AUs                      | Multiple (6)     | 1, 2, 4, 6, 9, 12, 25 | Rank SVMs      | SASE-FE       | 73.00%    |
| Racoviteanu et al. (2019) | AlexNet CNN architecture on 12 AU intensities to obtain the features in a transfer learning manner | Multiple (6)     | 1, 2, 4-6, 9, 12, 15, 17, 20, 25, 26 | SVM            | DISFA, SPOS  | 72.10%    |

Table 2. A brief overview of muscle movement based SVP detection methods.
changes by tracking a series of facial fiducial markers with a dental perspective. (Mandal and Ouarti 2017) fused subtle (micro) emotions on SASE-FE database, with an average accuracy of 68%. (Mandal et al. 2016) achieved 74.68% using combined features from eyes and lips, slightly better than using only the lips (with 73.44%) on the UvA-NEMO smile database. A different hybrid method in (Kulkarni et al. 2018) combined learned static CNN representations from still images with facial landmark trajectories, and achieved promising performance not only in emotion recognition, but also in detecting genuine and posed facial expressions on the BABE-FE database with data augmentation (70.2%)

Table 3. A brief overview of spatial patterns based SVP detection methods.

| Reference | Method (features) | Expression | Classification | Database | Accuracy |
|-----------|-------------------|------------|----------------|----------|----------|
| Valstar et al. (2007) | Fusing temporal dynamics of head (6 features), face (12 points), and shoulder (5 points) modalities | Smile | GentleSVM-Sigmoid | MMI (202) | 94.00% |
| Van Der Geld et al. (2008) | Analyzing tooth display, lip position and smile width in a dental perspective | Smile | / | Self-collected | / |
| Dibeklioğlu et al. (2010) | Distance-based and angular features for eyelid movements | Smile | Naive Bayes | BBC, CK | 91.00% |
| Dibeklioğlu et al. (2012) | Fusing the dynamics of eyelid, cheek, and lip corner movements | Smile | linear SVM | UvA-NEMO, SPOS, MMI | 92.10% |
| Dibeklioğlu et al. (2015) | Dynamics of eyelid, cheek, and lip corner movements | Smile | SVM | UvA-NEMO, SPOS, SASE-FE | 89.69% |
| Wang et al. (2015, 2016) | Spatial pattern modeling based on multiple RBMs and incorporating gender and expression categories as privileged information | Multiple (6) RBMs | Bayesian Networks | USTC-NVIE, MMI | 92.61% |
| Gan et al. (2017) | Spatial patterns based on Latent Regression Bayesian Network from he displacements of facial feature points | Multiple (6) | Bayesian Networks | USTC-NVIE | 98.74% |
| Huynh and Kim (2017) | Spatial-temporal features using mirror neuron modeling and LSTM with parametric bias from facial landmarks | Multiple (6) | Gradient boosting | SASE-FE | 66.70% |
| Wang et al. (2019) | Universal spatial patterns and complicated temporal patterns using IT-RBM dynamic model | Multiple (6) | Bayesian network | SPOS, DISFA+ | 83.76% |

Table 4. A brief overview of visual features based SVP detection methods.

| Reference | Method (features) | Expression | Classification | Database | Accuracy |
|-----------|-------------------|------------|----------------|----------|----------|
| Littlewort et al. (2009) | Gabor features based | Pain | Gaussian SVM | UvA-NEMO | 88.00% |
| Pfister et al. (2011) | Spatiotemporal local texture descriptor (CLBP-TOP), fusing the NIR and VIS modalities | Multiple (6) | MKL | SPOS | 80.00% |
| Liu and Wang (2012) | Temperature features from Infrared thermal images | Multiple (6) | Bayesian Networks | USTC-NVIE | 76.70% |
| Gan et al. (2015) | A two-layer deep Boltzmann machine model based on several features: using CNN face features, LPQ, dense optical flow and HOG, and HOG with the best result | Multiple (6) | Haarcascades | SPOS, USTC-NVIE | 91.73% |
| Mandal et al. (2016) | Learned features from CNN and spatial-temporal features | Multiple (6) | Linear SVM | UvA-NEMO | 78.14% |
| Xu et al. (2017) | Learned features based on CNN from difference image of onset and apex images | Multiple (6) | Linear SVM | SPOS, USTC-NVIE, BioVid Heat Pain, STOIC | 97.98% |
| Tavakolian et al. (2019) | Encoding the dynamic and appearance of a video into an image map based on spatiotemporal pooling, then using R-GAN model for discrimination | Pain | Softmax | UNBC-McMaster | 91.34% |

Table 5. A brief overview of hybrid methods for SVP detection.

| Reference | Method (features) | Expression | Classification | Database | Accuracy |
|-----------|-------------------|------------|----------------|----------|----------|
| Zhang et al. (2011) | SIFT appearance based features and FAP geometric features | Multiple (6) | RBF SVM | USTC-NVIE | 79.40% |
| Li et al. (2017) | Combining sequential geometric features based on facial landmarks and texture features using HOG | Multiple (6) | Sigmoid | SASE-FE | 68% |
| Mandal and Ouarti (2017) | Fusing subtle (micro) changes by tracking a series of facial fiducial markers with local and global motion based on dense optical flow | Smile | SVM | UvA-NEMO | 74.68% |
| Kulkarni et al. (2018) | Combining learned static CNN representations from still images with facial landmark trajectories | Multiple (6) | Linear SVM | SASE-FE | 70.20% |
| Saito et al. (2020) | Combining hardware (16 sensors embedded with the smart eyewear) with software-based method to get geometric and temporal features | Smile | Linear SVM | Self-collected | 94.60% |

with the worst of 77.2%) on the USTC-NVIE database. Sequential geometric features based on facial landmarks and texture features using HOG were combined in (Li et al. 2017). A temporal attention gated model is designed for HOG features, combining with LSTM autoencoder (eLSTM) to capture discriminative features from facial landmark sequences. The proposed model performed well on most emotions on SASE-FE database, with an average accuracy of 68%. (Mandal and Ouarti 2017) fused subtle (micro) changes by tracking a series of facial fiducial markers with local and global motion based on dense optical flow, and achieved 74.68% using combined features from eyes and lips, slightly better than using only the lips (with 73.44%) and using only the eyes (with 71.14%) on the UvA-NEMO smile database. A different hybrid method in (Kulkarni et al. 2018) combined learned static CNN representations from still images with facial landmark trajectories, and achieved promising performance not only in emotion recognition, but also in detecting genuine and posed facial expressions on the BABE-FE database with data augmentation (70.2%
accuracy). Most recently, (Saito et al. 2020) combined hardware (16 sensors embedded with the smart eye-wear) with software-based method to get geometric and temporal features to classify smiles into either spontaneous or posed, with an accuracy of 94.6% on their own database. See Table 5 for a brief summary of these hybrid SVP facial expression detection methods.

**Discussions**

Through our systematic literature survey, we have identified a number of factors that will influence the performance of SVP facial expression detection methods. To gain a deeper understanding, we will summarize and discuss these confounding factors as well as some insights and challenges in this section.

**Influence of features.** It is clear that the features extracted for distinguishing between posed and spontaneous facial expressions play a key role in detection performance. Most methods have explored temporal dynamics of different features for effective detection. We can observe from Tables 2-5 that the detection performance varies a lot among different algorithms on the same database. The visual learned features from difference images proposed by (Gan et al. 2015) and (Xu et al. 2017) in Table 4 performed better than muscle movement and spatial patterns based methods on SPOS database, while on USTC-NIVIE database and smile SVP database UvA-NEMO, spatial patterns based methods achieve slightly higher accuracy than visual features, and significantly higher than other kinds of methods. Overall, visual features based and spatial patterns methods show more promising detection abilities; but there still lacks a consensus about what type of features will be optimal for the task of SVP detection.

**Influence of facial regions.** Each emotion has its own discriminative facial regions, which can be used not only in emotion recognition but also in posed and genuine classification. As mentioned above, study in (Zhang et al. 2011) has found that in SVP emotion detection, the mouth region is important for sadness; the nose is more important for surprise; both the nose and mouth regions are important for disgust, fear, happiness, while the eyebrows, eyes, nose, mouth are all important for anger. Another study (Liu and Wang 2012) also explored different facial regions, including the forehead, eyes, nose, cheek, and mouth. Experiments results have shown that the forehead and cheek performed better than the other regions for most facial expressions (disgust, fear, sadness, and surprise), while the mouth region performed the worst for most facial expressions. Moreover, fusing all these regions achieved the best performance. In SVP smile detection, it was observed in (Dibeklioğlu et al. 2012) that the discriminative power of eyelid region is better than cheek and lip corners. A different study in Mandal and Ouarti (2017) has found that lip-region features (with 73.44% on UvA-NEMO) outperformed the eye-region features (with 71.14%), while the combined features performed the best with 74.68% accuracy. Overall, fusion of multiple facial regions can improve the detection performance over individual features. Besides, varying video temporal segments (i.e., onset, apex, and offset) for feature extraction also lead to different performance. Several studies (Cohn and Schmidt 2003; Dibeklioğlu et al. 2012) have demonstrated the onset phase performs best among individual phases in SVP facial expression detection.

**Influence of emotions.** Due to the differences in activation of muscles, such as with different intensities and in different facial regions, each emotion has different difficulty levels in SVP expression detection. For example, happiness and anger can activate obvious muscles around eye and mouth regions, which has been widely studied for feature extraction. Based on appearance and geometric features, (Zhang et al. 2011) found that surprise is the easiest emotion (with 83.4% accuracy on USTC-NIVIE), followed by happiness with 80.5%, while disgust is the most difficult one (with 76.1%). Similarly, Kulkarni et al. (2018) achieved better results in detecting SVP happiness (with 71.05% accuracy) and anger (with 69.40%), but worse results in disgust (with 63.05%) and contempt (with 60.85%) on SASE-FE dataset. On the contrary, (Li et al. 2017) obtained the highest accuracy (of 80%) for both disgust and happy, while 50% for contempt on SASE-FE dataset. Overall, SVP happiness is relatively easy to recognize. In the future, how to improve the generalization ability of SVP detection on multiple universal facial expressions, or improve the performance on specific emotion based on its unique facial features, deserves more studies.

**Influence of databases.** The databases for SVP facial expressions also play a significant role in benchmarking effectiveness and practicality of different detection schemes. From Tables 2-5, it can be observed that the detection performance of the same detection method can vary wildly on different databases. In addition to direct influence of the data size and data quality, studies have also found the influence of subjects in terms of both age and gender. (Dibeklioğlu et al. 2012) explored the effect of subject age by splitting the UvA-NEMO smile database into young (age < 18) and adults (age ≥ 18 years), and found that eyelid- and-cheek features provided more reliable classification for adults, while lip-corner features performed better on young people. They further explored the gender effect in method (Dibeklioğlu et al. 2015) and showed that results on males were all better than females using different facial region features. This can be attributed to the reasons that male subjects have more discriminative geometric features (distances between different landmark pairs) than females. They also improved their detection performance by using age or gender as labels. Similarly, (Wang et al. 2019) considered the influence of gender, and incorporated it as privileged information for performance improvement. To sum up, the findings on age and gender influence can not only provide suggestions for SVP facial expression database collection to take subject distribution into consideration, but also inspire researchers to design more effective and practical detection methods taking advantage of data properties.

**Influence of classifiers.** The classifier has a great effect on most classification tasks, which has also been explored by researchers in distinction between spontaneous and posed facial expressions. (Dibeklioğlu et al. 2010) assessed the reliability of their features with continuous HMM, k-Nearest Neighbor (k-NN) and naive Bayes classifier, and the highest classification rate was achieved by naive Bayes classifier on two datasets. (Pfister et al. 2011) compared
support vector machine (SVM), Multiple Kernel Learning (MKL), and Random Forest decision tree (RF) classifier, and found RF outperformed SVM and MKL based on CLBP-TOP features on SPOS database. (Dibeklioğlu et al. 2015) compared Linear Discriminant, Logistic Regression, k-NN, Naïve Bayes, and SVM classifiers on UvA-NEMO smile dataset, and showed the outstanding performance of SVM classifier under all testing scenarios. (Racoviteanu et al. 2019) also used SVM, combined with a Hard Negative Mining (HNM) paradigm, to produce the best performance among RF, SVM, and Multi-Layer Perceptron (MLP) classifiers. Overall, as the most widely-used classifier, SVM can provide outstanding performance on several databases. Whether recently developed deep learning-based classifiers can achieve further performance improvement remains to be explored.

**Influence of modalities of images.** In addition to visible images/videos, some studies have shown the impact of different modalities on improving the detection performance. (Pfister et al. 2011) illustrated that the performance of fusion of NIR with visible images (with 80.0% accuracy) is better than using single NIR (with 78.2%) or visible images (with 72.0%) on SPOS dataset. Although special devices are needed for data acquisition, the advantages of different modalities in revealing subtle features deserve further investigation. It is also plausible to combine the information contained in multiple modalities for detection performance improvement.

**Performance differences of spontaneous and posed expressions.** Last but not the least, several studies have observed the apparent gap of performance between posed facial expressions detection and genuine ones. For example, based on visual features, (Liu and Wang 2012) found that it is much easier to distinguish all posed expressions (with 90.8% accuracy) than genuine ones (62.6%) on USTC-NIVE database. Similarly, (Mandal et al. 2016) also achieved higher classification accuracy of posed smiles than spontaneous ones (with over 10% gaps) on UvA-NEMO dataset. However, two hybrid methods (Mandal and Ouardi 2017; Kulkarni et al. 2018) both obtained higher accuracy in detecting genuine facial expressions than posed ones, with a 6% gap in method (Mandal and Ouardi 2017) on UvA-NEMO Smile database, while an average of 7.9% gap in method (Kulkarni et al. 2018) on SASE-FE database. Such inconsistent differences can be attributed to the influences of both feature extraction methods and databases.

**Conclusions**

With the emerging and increasingly supported theory that facial expressions do not always reflect our genuine feelings, automatic detection of spontaneous and posed facial expressions have become increasingly important in human behaviour analysis. This survey has summarized recent advances of SVP facial expression detection over the past two decades. A total of eleven databases and about thirty detection methods have been reviewed and analyzed. Particularly, we have identified and discussed several influencing factors of SVP detection methods to gain a deeper understanding of this nascent field. This review paper is expected to serve as a good starting point for researchers who consider developing automatic and effective models for genuine and posed facial expression recognition.

One area that has not been covered by this survey is the 3D dynamic facial expression databases (Zhang et al. 2013; Sandbach et al. 2012). As 3D scanning technology (e.g., Kinect and LIDAR) rapidly advances, SVP detection from 3D instead of 2D data might become feasible in the near future. Can 3D information facilitate the challenging task of SVP detection? It remains to be found out. Research on SVP detection also has connections with other potential applications such as Parkinson’s disease Smith et al. (1996), deception detection Granhag and Strömwall (2004), and alexithymia McDonald and Prkachin (1990). More sophisticated computational tools such as deep learning based might help boost the research progress in SVP detection. It is likely that the field of facial expression recognition and affective computing will continue growing in the new decade.

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