Towards Micro-expression Recognition Through Pyramid of Uniform Temporal Local Binary Pattern Features

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Abstract. Compared to macro-expressions, recognizing micro-expres-sions is more challenging due to low intensity and their brief duration. To deal with this issue, the present paper proposes a facial micro-expression recognition approach based on the pyramid of uniform Temporal Local Binary Pattern (PTLBP^{u2}) features for describing the appearance motion changes in time through video stream. Unlike the majority of approaches that use a high dimensional feature space, the proposed approach is based on a low dimensional space with only 83 features. Compared to the most recent facial micro-expression recognition approaches, our approach proves its effectiveness with an accuracy rate reaching 66.40% on Casme II dataset. A study of the ability of a macro-expression model to recognize micro-expression shows that it is more efficient to recognize certain micro-expressions than others.

Keywords: Micro-expressions · PTLBP^{u2} · Pyramid representation · Low-dimensional feature space · Random Forests (RF) · Macro-expressions

1 Introduction

The automatic facial micro-expression analysis represents an essential role in various applications [15,24] such as human-computer intelligent interfaces, lies detection, psychotherapy, clinical diagnosis, marketing, and many others. Compared to basic facial expressions, the micro-expressions are totally involuntary, and difficult to recognize due to their low intensity and their brief duration which is between 1/25 and 1/5 of a second [9]. Thereby, it is very difficult to recognize a facial micro-expression by the naked eye. For several years, a great effort has been devoted to automatic facial micro-expression recognition.

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Generally, automatic micro-expression systems consist on three main steps: face detection and tracking, feature detection, and micro-expression classification. Feature detection is the most crucial step due to the low change in the intensity of micro-expressions. In this respect, many methods have been proposed in the literature. They can be roughly divided into motion-based methods and appearance-based methods [21].

The motion-based methods, which often use the optical flow [3], consist in measuring the orientation of micro-expressions motion changes locally and between consecutive frames in a video stream. In this context, several methods have been conducted as the Delaunay-based Temporal Coding Model (DTCM) [22], the Interval Temporal Bayesian Network (ITBM) [22], the Main Directional Mean Optical flow (MDMO) [20], the Facial Dynamics Map (FDM) [34]. These methods are vulnerable to the illuminations, noises and resolutions [21].

The appearance-based methods involve various statistics on the pixels' values [33] in order to describe intensity and textural information such as wrinkles, furrows, and other patterns that are caused by emotion [23]. Several representations were used to describe the micro-expression such as the Gabor filters [36], the 2D Gabor filter and Sparse Representation (2DGSR) [38], the Discriminant Tensor Subspace Analysis (DTSA) [30], and the Local binary Pattern on Three Orthogonal Planes (LBP-TOP) [37]. The latter was used in several approaches of micro-expression recognition [8,29,31,32,35]. Moreover, several variants of LBP-TOP are proposed in the literature to amplify the micro-expression information in a very brief time such as the Encoding LBP [27], the Spatiotemporal LBP with Integral Projection (STLBP-IP) [12], the Discriminative Spatiotemporal Local Binary Pattern based on an Improved Integral Projection (DiSTLBP-IIP) [13] and the Spatio-Temporal Completed Local Quantized Patterns (STCLQP) [14]. The appearance-based methods are tolerant of illumination changes [11]. Therefore, appearance based methods, especially those that apply LBP-TOP, have become more popular in the literature on micro-expression recognition. These methods present a huge number of features and show a low accuracy rate. Unlike the majority of related works that are based on a high-dimensional spatio-temporal feature space, the purpose of this paper is to propose a facial micro-expression recognition approach based on a low-dimensional temporal feature space. Encouraged by the performance of our proposed feature space namely the Pyramid of uniform Temporal Local Binary Pattern (PTLBP^{u2}) [1] used for the facial macro-expressions recognition, Our contributions are cited as follows:

- Representing the facial micro-expression using PTLBP^{u2} for facial micro-expression recognition. In fact, PTLBP^{u2} presents video sequences frames according to a pyramid of levels to define sub-region cuboids at different resolutions. Unlike LBP-TOP that describes only the local texture, PTLBP^{u2} provides more appearance motion change features through different spatial layout of texture (i.e., from sub-region cuboid at different resolutions).
- Studying the ability of a facial macro-expression recognition model to recognize micro-expressions.

The remainder of this paper is organized as follows. Section 2 describes an overview of the proposed approach. Section 3 and Sect. 4 present, respectively, the feature detection and sub-regions selection steps. Section 5 is devoted to detail experimental series and to compare the effectiveness of our proposal with other related works. Section 6 draws a conclusion and offers some perspectives.

2 Proposed Approach

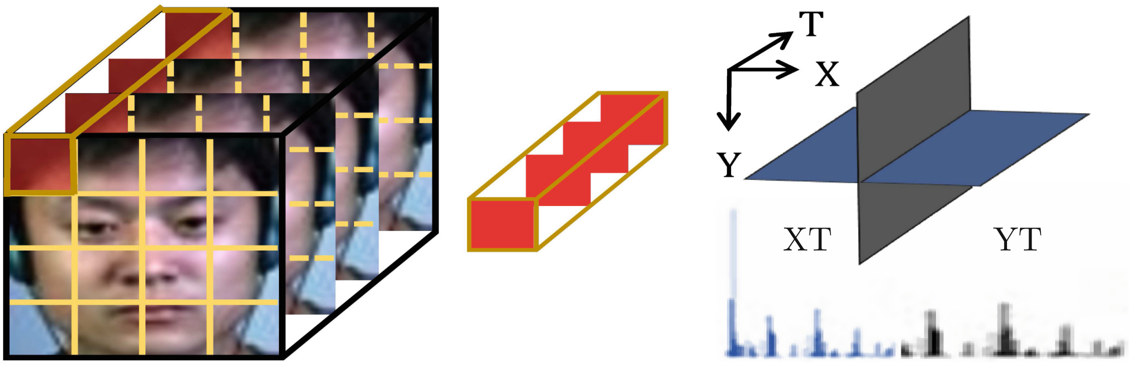
To automatically recognize micro-expressions taken from frontal-face video sequences, we rely on a dynamic feature-based approach that consists in defining a temporal low-dimensional feature space through the levels of a pyramidal representation. The proposed approach is performed in five main steps:

1. Localize the face of the subject in accordance with a landmark-based method. The Active Shape Model (ASM) [6] is used to detect 68 landmarks on the face of the first frame, and then the Local Weighted Mean (LWM) [10] is applied to track them on the remaining frames. ASM is used because it allows rapid and accurate location of the boundary of objects.
2. Detect PTLBP^{u2} features (Sect. 3) from sub-region cuboids at different resolutions according to a pyramid representation.
3. Remove irrelevant and redundant features using a Sequential Forward Selection-based method (SFS) [1], that selects the discriminating sub-regions.
4. Reduce the dimension of the space feature by applying Principal Component Analysis (PCA) [2]. The number of principal components is determined by the Maximum Likelihood Estimator [18].
5. Apply an adequate supervised learning method to create a robust classifier.

3 Feature Detection Using PTLBP^{u2}

To detect features, we rely on a pyramidal-based spatial-temporal representation (PTLBP^{u2}) [1]. The main steps for the PTLBP^{u2} feature detection are as follows:

1. Represent each video sequence by n levels. For each level i, subdividing all the sequences into $2^i \times 2^i$ equivalent cuboids. For example, the number of cuboids of level 2 is $4 \times 4 = 16$ cuboids and for level 3 is 64 cuboids (Fig. 1). The choice of the best combination of levels is conducted in Sect. 5.
2. For each cuboid, calculate the histograms of uniform Local Binary Pattern (LBP^{u2}) using only vertical planes XT and YT [37]. It is worth noting that each histogram is quantified into 59 bins. Each one among the first 58 bins represents the occurrence of each uniform LBP value (i.e., if the binary code of the LBP value obtained contains at most two bitwise transitions from 0 to 1 or from 1 to 0), and the last bin represents the occurrence of a non-uniform LBP value.
3. For each level i, join XT and YT histograms of LBP^{u2} of each cuboid in order to create the final PTLBP^{u2} feature space. The dimension of the feature space of the i^{th} level is equal to $2 \times 59 \times \sum_l 4^l$.



(a) (b) (c)

Fig. 1. PTLBP^{u2} feature detection. (a) pyramid representation of level 2, (b) Cuboid, (c) XT and YT histograms of LBP^{u2} of the cuboid

4 Sub-regions Selection

This stage aims to select the most discriminating sub-region cuboids. For this purpose, we apply an adapted Wrapper method based on SFS [1]. The process to follow can be formulated by four steps:

1. Generate N classifiers by applying Sequential Minimal Optimization (SMO) algorithm [17,26] with polynomial kernel, each one, on PTLBP^{u2} space from a sub-region cuboid among the N sub-regions of the pyramid levels considered. The leave-one-subject-out folds (LOSO) protocol is used to estimate the performance for each classifier.
2. Sort the N sub-regions according to the performance of their classifiers.
3. Create $N-1$ classifiers that correspond to $N-1$ combinations of sub-regions. The first combination contains the first and the second best sub-regions. The second combination contains the first, the second, and the third best sub-regions, and so on.
4. Select the best combination that corresponds to the best classifier.

5 Experimental Results

We conducted micro-expression recognition experiments with reference to three datasets: the micro-expression dataset Casme II [35], and the macro-expressions datasets: extended Cohn-Kanade (CK+) [16] and MMI [25]. The analysis proposed in this study is based on the following two classifiers: the Sequential Minimal Optimization (SMO) algorithm using a 1-degree polynomial kernel and 1-vs-1 strategy for resolving the multi-classification challenge [17,26] and Random Forests (RF) algorithm [5]. Two experiment series have been proposed. The first one consists in evaluating the proposed approach of micro-expression recognition on Casme II dataset. The second one consists in studying the ability of a macro-expression recognition model to recognize micro-expressions. It's worth noting that the algorithms of feature detection and selection have been developed, using Matlab R2015a. Weka is applied to generate and evaluate the classifiers used in expression classification.

5.1 Micro-expression Recognition Based on PTLBP^{u2}

The Dataset and Protocol of Evaluation. Casme II [35] represents the largest and most widely used dataset to date with samples recorded using high frame-rate cameras (200 fps) [23] and a spatial resolution which is equal to 280×340 pixels. This dataset includes 256 frontal pose micro-expression video sequences captured using 26 subjects. It presents seven micro-expressions: 63 "disgust" (DI), 27 "repression" (RE), 32 "happiness" (HA), 25 "surprise" (SU), 7 "sadness" (SA), 2 "fear" (FE) and 100 "others" (OT). In our study, we excluded the "sadness" and "fear" micro-expressions because they are represented by a little number of sequences. Therefore, we considered only the remaining five classes presented by 247 video sequences. After face detection and tracking, we resized each frame to 280×336 pixels to create equal sub-regions in the pyramid presentation. The performance of classifiers is evaluated under leave-one-subject-out folds (LOSO) protocol. Indeed, one subject is used for the test and the others are used for the training. This task is repeated until each subject will be used once as the test set. The evaluation measure used is the weighted average of the test classification of the different subjects.

Pyramid Representation: The Best Combination of Levels. As our goal is to create a low dimensional space, we considered only the three first levels of a pyramid. Indeed, using more than the three first levels increases the size of feature space remarkably. To determine the best combination of levels, we generated up to four classifiers, each one by applying SMO on features of sub-region cuboids of (1) "level 1+level 2", (2) "level 1+level 3", (3) "level 2+level 3", and (4) "level 1+level 2+level 3". Table 1 depicts the performances of micro-expression recognition using different combinations of pyramid levels. It shows that using the sub-region cuboids of level 2 and level 3 of the pyramid records the best classification accuracy. The results thus obtained are compatible with those obtained in macro-expressions recognition [1].

Table 1. Classification accuracy using different combinations of pyramid levels on Casme II dataset

	level 1+level 2	level 1+level 3	level 2+level 3	level 1+level 2+level3
Accuracy (%)	59.11	60.73	62.75	61.94

Selection of the Most Discriminating Sub-regions. As level 2 and level 3 contain 80 sub-regions, we generated 79 classifiers by applying SMO on each combination of sub-regions (Sect. 4). In contrast to our macro-expressions recognition approach [1], the selection of sub-regions decreases the performance of the classifier. In fact, the best combination is the one that uses all the sub-regions of level 2 and level 3. This can be explained by the fact that the appearance motion changes induced by micro-expressions are brief and not obvious to detect using only few sub-regions. So, we considered all the sub-regions of level 2 and level 3 and we studied if the creation of new features using PCA can capture the important information more effectively than the original ones. Table 2 shows the impact of using PCA on the micro-expression recognition accuracy.

Table 2. Classification accuracy of SMO classifiers with and without feature extraction

	Number of features	Classification accuracy (%)
PTLBP^{u2}	9440	62.75
$\mathrm{PCA}[\mathrm{PTLBP}^{u2}]$	83	64.37

Unlike the sub-regions selection, the creation of a new space using PCA increases in the performance of the classifier and decreases in the number of features. Indeed, by using only 83 out of 9440 features, the classification accuracy increased from 62.75% to 64.37%.

Table 3 presents the confusion matrices of the SMO classifiers respectively without and with PCA. Each value presented in the diagonal of the matrix, corresponds to the recall measure of each micro-expression class. The results obtained show a remarkable increase of 7.68% and 6.33% in classifying, respectively, "happiness" and "others" micro-expressions. Note that the increase rate is defined as "the recall accuracy as measured for each class" understood as a measure of a micro-expression accuracy using the classifier with PCA divided by the corresponding classifier without PCA, subtracted by 1. A slight increase in recall accuracy of the "disgust" micro-expression is shown. In contrast, a decrease of 13.34% is recorded on the recall accuracy of "repression" micro-expressions. Another issue that can be deduced from Table 3 is the high rate of misclassification for certain micro-expressions. For example, 52% of "surprise" are recognized as "others". 25% of "Happiness" micro-expressions are recognized as "repression". Therefore, the misclassification of these classes can be explained by the small number of video sequences that represent them and the similarity between these micro-expressions. In contrast, the classifier shows an excellent performance in the recognition of "others" class. This can be explained by the imbalanced distribution of the different classes. In fact, the class "others" is presented by 100 out of 247 video sequences. So, to reduce the global error, SMO can classify the majority class ("others") without taking into account the rest of classes.

Random Forests for Micro-expression Recognition. The goal of this section is to study if an ensemble learning method can improve the classification accuracy rate. We will rely on Random Forests (RF) [5] as an ensemble method because it has been widely used in pattern recognition [7,28].

RF combines a large number of binary CART decision tree [4] with bagging concepts (i.e., bootstrap aggregating) to avoid the over-fitting of a simple tree.

Table 3. LOSO confusion matrices of SMO classifier generated by PTLBP^{u2} on Casme II dataset

Without PCA					
	HA	OT	RE	DI	SU
HA	**40,63%**	18.75%	21.88%	15.63%	3.13%
OT	5.00%	**79.00%**	2.00%	14.00%	0.00%
RE	22.22%	18.52%	**55.56%**	3.70%	0.00%
DI	0.00%	26.98%	1.59%	**61.90%**	9.52%
SU	8.00%	36.00%	0.00%	20.00%	**36.00%**
With PCA					
	HA	OT	RE	DI	SU
HA	**43.75%**	12.50%	25.00%	18.75%	0.00%
OT	3.00%	**84.00%**	1.00%	12.00%	0.00%
RE	22.22%	18.52%	**48.15%**	3.70%	7.41%
DI	1.59%	26.98%	3.17%	**63.49%**	4.76%
SU	4.00%	52.00%	4.00%	8.00%	**32.00%**

Formally, to fit each tree of the forest, we first randomly selected with replacement about 63% of the video sequences as the learning set (in-bag) and the remaining video sequences as a set of out-of-bag (OOB). This set is used generally to estimate the performance of the model. Then, we applied CART algorithm on feature space of in-bag video sequences with adopting Gini's entropy in order to split nodes. Predictions of micro-expressions for test samples are achieved by taking the decision from all trees with majority vote. Typically, the number of trees in a forest depends on the size and the nature of the learning set. An optimal number of trees can be obtained by estimating the overall OOB classification accuracy of RF for different numbers of trees. Plotting the out-of-bag classification accuracy curve versus the number of trees, the maximal value of OOB classification accuracy corresponds to 69.23% with 210 trees. Under LOSO validation protocol, The RF model records 66.40% of overall classification accuracy which exceeds the performance of SMO classifier. So, using RF as the supervised learning method is an effective way to improve the micro-expression recognition.

Table 4 depicts the confusion matrix of the five micro-expressions using the RF classifier. There is a good match between the results obtained by applying SMO and RF. Compared to SMO classifier, using RF as a learning method allows to improve the recognition of "surprise" micro-expressions. Indeed, the corresponding recall increases from 32.00% to 48.00%. It is worth noting that the same phenomena of confusion between micro-expressions are observed specially for the class "repression" where 37.04% are recognized as "others".

Table 4. LOSO confusion matrix of RF classifier generated by PCA[PTLBP^{u2}] on Casme II dataset

	HA	OT	RE	DI	SU
HA	**46.88%**	28.13%	3.13%	21.88%	0.00%
OT	6.00%	**84.00%**	0.00%	9.00%	1.00%
RE	3.70%	37.04%	**44.44%**	0.00%	14.81%
DI	4.76%	23.81%	3.17%	**65.08%**	3.17%
SU	16.00%	36.00%	0.00%	0.00%	**48.00%**

Comparison with the State-of-the-Art Works. In this section, we compare our approach based on PCA[PTLBP^{u2}] feature space and RF with other state-of-the-art approaches. It is important to mention that we limit our comparison to the most recent approaches that use exactly the same experimental conditions as ours. In other words, all the mentioned approaches in Table 5 use LOSO validation protocol and only 247 video sequences, from Casme II, that correspond to the five micro-expression classes namely "disgust", "repression", "happiness", "surprise", and "others". Specifically, we compare our approach with the following state-of-the-art approaches: LBP-TOP [35], STLBP-IP [12], DiSTLBP-IIP [13], FDM [34], 2DGSR [38] and Bi-WOOF [19]. These approaches can be divided into two categories: (i) appearance-based methods [12,13,35,38] and motion-based methods [19,34]. From Table 5, we can conclude that the appearance-based methods are more efficient than the motion-based methods in the recognition of micro-facial expression features. Indeed, the classification accuracy of appearance-based methods varies from 59.51% to 64.88% contrary to the classification accuracy of the motion based methods that does not exceed 58.85%. According to the classification accuracy rate, our approach shows the best performance. The enhancement of classification accuracy varies from 1.62% (our approach versus 2DGSR [38]) to 20.47% (our approach versus FDM [34]). The enhancement is more visible when we compare the different approaches according to the number of features used. To our knowledge, our approach is the first to recognize facial micro-expression using only 83 features.

5.2 A Facial Macro-expression Model to Recognize Micro-expressions

The goal of the second experiment series is to study the ability of our macro-expression model [1] to recognize micro-expressions. As CK+ [16] and MMI [25] represent the most known macro-expression data sets, we will use them to create two macro-expression models and then, test them on Casme II datasets. There are three common expressions of these datasets namely: "surprise", "disgust" and "happiness". So, for each dataset, we select only the video-sequences that represent these expressions. For Casme II, we obtain 25 video sequences of "surprise", 63 video sequences of "disgust", and 32 video sequences of

Table 5. Comparison of the proposed approach with some state-of-the-art works

	Number of features	Classification accuracy (%)
LBP-TOP [35]	4425	63.41
STLBP-IP [12]	12744	59.51
DiSTLBP-IIP [13]	3000	64.78
FDM [34]	-	45.93
2DGSR [38]	-	64.88
Bi-WOOF [19]	288	58.85
Proposed approach	**83**	**66.40**

"happiness". For CK+ (resp. MMI), we obtain 83 (resp. 37) video sequences of "surprise", 69 (resp. 42) video sequences of "disgust", and 59 (resp. 31) video sequences of "happiness". The classifications are performed by RF with n trees on PCA[PTLBP^{u2}] feature space. To obtain a robust classifier for each model, we determined empirically the number n of trees based on the OOB classification accuracy computed as a function of the number of trees. For CK+ (resp. MMI), 150 (resp. 200) trees achieve the best OOB classification accuracy is equal to 93.83% (resp. 81.71%). Using LOSO as a validation protocol, the overall classification accuracy for CK+ (resp. MMI) is 62.5% (resp.40.83%). Table 6 details the confusion matrices obtained. From these tables, it can be seen that a macro-expression model is able to adequately recognize the "disgust" micro-expression with an accuracy classification reaching 84.38% (using CK+), but cannot recognize "surprise" micro-expressions. This can be explained by the difference in the appearance motion changes between macro and micro-expression of surprise. Indeed, in a macro-expression surprise the motion changes are principally on the mouth in contrast to the micro-expressions that are generally on the extremities of the eyes, and eyebrows. When we compare the two different models, we can conclude that the CK+ based model is more appropriate than the MMI based model to recognize micro-expressions.

Table 6. Confusion matrices of applying independently PCA[PTLBP^{u2}] features of CK+ and MMI datasets on RF classifier generated by Casme II dataset

CK+ as train set			
	HA	DI	SU
HA	**59.38%**	34.38%	6.25%
DI	9.52%	**84.13%**	6.35%
SU	20.00%	68.00%	**12.00%**

MMI as train set			
	HA	DI	SU
HA	**25.00%**	34.38%	6.25%
DI	26.98%	**61.90%**	8.00%
SU	32.00%	60.00%	**8.00%**

6 Conclusion

The facial micro-expression recognition is one of the most challenging research fields in pattern recognition. To meet this challenge, some studies are based on motion features; others use appearance features. Similarly to the latter category, this work presents a facial micro-expression approach based on the Pyramid of uniform Temporal Local Binary Pattern (PTLBP^{u2}) [1]. Feature extraction is conducted to transform the feature space to a low- dimension space of principal components. SMO and RF are tested to create a robust classifier. Extensive experimental studies and comparisons were carried out in order to prove the effectiveness of our approach. The main contributions of this study are summarized in the following points:

- First, proposing a facial micro-expression approach based on a low dimensional feature space, proving that applying PCA on the Pyramid of uniform Temporal Local Binary Pattern and using RF as a learning method can improve the recognition rate.
- Second, comparing the proposed approach with competitive approaches proposed for micro-expression recognition has proved its performance essentially in terms of a number of features used.
- Third, deducing that a facial macro-expression model is able to recognize some micro-expressions like disgust, not with standing its poor performance in the recognition of other micro-expressions such as surprise.

This study opens lots of interesting research perspectives to improve the efficiency of our approach. As the selection of sub-regions decreases the performance of the classifier, we plan to explore the impact of selecting the most discriminating features on the performance of the classifier. Also, we have to focus on the problem of imbalanced data presented by the micro-expression datasets and explore if an adapted supervised learning method for this problem can improve the efficiency of our approach. Finally, we plan to explore the benefits of deep learning and deep transfer learning for micro-expression recognition.

References

1. Abdallah, T.B., Guermazi, R., Hammami, M.: Facial-expression recognition based on a low-dimensional temporal feature space. Multimedia Tools Appl. **77**(15), 19455–19479 (2018)
2. Abdi, H., Williams, L.J.: Principal component analysis. Wiley Interdisc. Rev. Comput. Stat. **2**(4), 443–459 (2010)
3. Beauchemin, S.S., Barron, J.L.: The computation of optical flow. J. ACM Comput. Surv. **27**(3), 433–466 (1995)
4. Breiman, L.: Bagging predictors. Mach. Learn. **24**(2), 123–140 (1996). https://doi.org/10.1023/A:1018054314350
5. Breiman, L.: Random forests. Mach. Learn. **45**(1), 5–32 (2001)
6. Cootes, T., Taylor, C., Cooper, D., Graham, J.: Active shape models-their training and application. Comput. Vis. Image Underst. **61**(1), 38–59 (1995)

7. Denisko, D., Hoffman, M.M.: Classification and interaction in random forests. Proc. Nat. Acad. Sci. **115**(8), 1690–1692 (2018)
8. Duan, X., Dai, Q., Wang, X., Wang, Y., Hua, Z.: Recognizing spontaneous micro-expression from eye region. Neurocomputing **217**, 27–36 (2016). sI: ALLSHC
9. Ekman, P.: Telling Lies – Clues to Deceit in the Marketplace, Politics and Marriage 3e (2009)
10. Goshtasby, A.: Image registration by local approximation methods. Image Vis. Comput. **6**(4), 255–261 (1988)
11. Heikkila, M., Pietikainen, M.: A texture-based method for modeling the background and detecting moving objects. IEEE Trans. Pattern Anal. Mach. Intell. **28**(4), 657–662 (2006)
12. Huang, X., Wang, S.J., Zhao, G., Piteikainen, M.: Facial micro-expression recognition using spatiotemporal local binary pattern with integral projection. In: Proceedings of the 2015 IEEE International Conference on Computer Vision Workshop (ICCVW), ICCVW 2015, pp. 1–9. IEEE Computer Society, Washington, DC (2015)
13. Huang, X., Wang, S., Liu, X., Zhao, G., Feng, X., Pietikäinen, M.: Spontaneous facial micro-expression recognition using discriminative spatiotemporal local binary pattern with an improved integral projection. CoRR abs/1608.02255 (2016). http://arxiv.org/abs/1608.02255
14. Huang, X., Zhao, G., Hong, X., Zheng, W., Pietikäinen, M.: Spontaneous facial micro-expression analysis using spatiotemporal completed local quantized patterns. Neurocomput. **175**(PA), 564–578 (2016)
15. IMOTIONS - BIOMETRIC RESEARCH PLATFORM: Facial expression analysis: the complete pocket guide (2016). https://imotions.com/blog/facial-expression-analysis
16. Kanade, T., Cohn, J.F., Tian, Y.: Comprehensive database for facial expression analysis. In: Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition, pp. 46–53 (2000)
17. Keerthi, S.S., Shevade, S.K., Bhattacharyya, C., Murthy, K.R.K.: Improvements to Platt's SMO algorithm for SVM classifier design. Neural Comput. **13**(3), 637–649 (2001)
18. Levina, E., Bickel, P.J.: Maximum likelihood estimation of intrinsic dimension. In: Advances in Neural Information Processing Systems, Cambridge, MA, USA, pp. 777–784 (2004)
19. Liong, S., See, J., Phan, R.C., Wong, K.: Less is more: micro-expression recognition from video using apex frame. J. Sig. Process. Image Commun. **62**, 82–92 (2018)
20. Liu, Y.J., Zhang, J.K., Yan, W.J., Wang, S.J., Zhao, G., Fu, X.: A main directional mean optical flow feature for spontaneous micro-expression recognition. IEEE Trans. Affect. Comput. **7**(4), 299–310 (2015)
21. Lu, H., Kpalma, K., Ronsin, J.: Motion descriptors for micro-expression recognition. Sig. Process. Image Commun. **67**, 108–117 (2018)
22. Lu, Z., Luo, Z., Zheng, H., Chen, J., Li, W.: A delaunay-based temporal coding model for micro-expression recognition. In: Jawahar, C., Shan, S. (eds.) Computer Vision - ACCV 2014 Workshops, pp. 698–711. Springer International Publishing, Cham (2015)
23. Oh, Y.H., See, J., Le Ngo, A.C., Phan, R.C.W., Baskaran, V.M.: A survey of automatic facial micro-expression analysis: databases, methods, and challenges. Front. Psychol. **9**, 11–28 (2018)
24. O'Sullivan, M., Frank, M.G., Hurley, C.M., Tiwana, J.: Police lie detection accuracy: the effect of lie scenario. J. Law Hum. Behav. **33**(6) (2009)

25. Pantic, M., Valstar, M., Rademaker, R., Maat, L.: Web-based database for facial expression analysis. In: Proceedings of the 13th ACM International Conference on Multimedia (2005)
26. Platt, J.: Fast training of support vector machines using sequential minimal optimization. In: Advances in Kernel Methods - Support Vector Learning. MIT Press (1998)
27. Ruiz-Hernandez, J.A., Pietikäinen, M.: Encoding local binary patterns using the reparametrization of the second order Gaussian jet. In: 2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), pp. 1–6 (2013)
28. Verikas, A., Gelzinis, A., Bacauskiene, M.: Mining data with random forests: a survey and results of new tests. J. Pattern Recogn. **44**(2), 330–49 (2011)
29. Wang, S.J., Yan, W.J., Li, X., Zhao, G., Fu, X.: Micro-expression recognition using dynamic textures on tensor independent color space. In: 2014 22nd International Conference on Pattern Recognition, pp. 4678–4683 (2014)
30. Wang, S.J., Chen, H.L., Yan, W.J., Chen, Y.H., Fu, X.: Face recognition and micro-expression recognition based on discriminant tensor subspace analysis plus extreme learning machine. Neural Process. Lett. **39**(1), 25–43 (2014)
31. Wang, Y., See, J., Oh, Y.H., Phan, R.C.W., Rahulamathavan, Y., Ling, H.C., Tan, S.W., Li, X.: Effective recognition of facial micro-expressions with video motion magnification. Multimedia Tools Appl. **76**(20), 21665–21690 (2017)
32. Wang, Y., See, J., Phan, R.C.W., Oh, Y.H.: LBP with six intersection points: reducing redundant information in LBP-TOP for micro-expression recognition. In: Cremers, D., Reid, I., Saito, H., Yang, M.H. (eds.) Computer Vision - ACCV 2014, pp. 525–537. Springer International Publishing, Cham (2015)
33. Wolf, L.: Face recognition, geometric vs. appearance-based, pp. 347–352. Springer, Boston (2009)
34. Xu, F., Zhang, J., Wang, J.Z.: Microexpression identification and categorization using a facial dynamics map. IEEE Trans. Affect. Comput. **8**(2), 254–267 (2017)
35. Yan, W.J., Li, X., Wang, S.J., Zhao, G., Liu, Y.J., Chen, Y.H., Fu, X.: CASME II: an improved spontaneous micro-expression database and the baseline evaluation. PLOS ONE **9**(1), 1–8 (2014)
36. Zhang, P., Ben, X., Yan, R., Wu, C., Guo, C.: Micro-expression recognition system. Optik Int. J. Light Electron Opt. **127**(3), 1395–1400 (2016)
37. Zhao, G., Pietikäinen, M.: Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Trans. Pattern Anal. Mach. Intell. **29**(6), 915–928 (2007)
38. Zheng, H.: Micro-expression recognition based on 2D Gabor filter and sparse representation. J. Phys. Conf. Ser. **787**(1) (2017)