https://doi.org/10.2352/ISSN.2470-1173.2021.11.HVEI-157

Micro-Expression Recognition with Noisy Labels

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Abstract

Facial micro-expressions are quick, involuntary and low intensity facial movements. An interest in detecting and recognizing micro-expressions arises from the fact that they are able to show person's genuine hidden emotions. The small and rapid facial muscle movements are often too difficult for a human to not only spot the occurring micro-expression but also be able to recognize the emotion correctly. Recently, a focus on developing better micro-expression recognition methods has been on models and architectures. However, we take a step back and go to the root of task, the data.

We thoroughly analyze the input data and notice that some of the data is noisy and possibly mislabelled. The authors of the micro-expression datasets have also acknowledged the possible problems in data labelling. Despite this, no attempts have been made to design models that take into account the potential mislabelled data in micro-expression recognition, to our best knowledge. In this paper, we explore new methods taking noisy labels into special account in an attempt to solve the problem. We propose a simple, yet efficient label refurbishing method and a data cleaning method for handling noisy labels. The data cleaning method achieves state-of-the-art results in the MEGC2019 composite dataset.

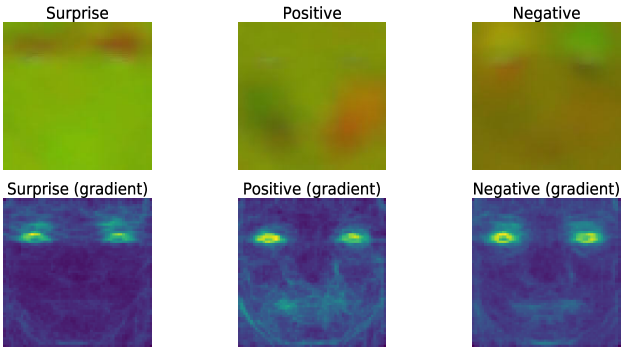


Figure 1. *Mean of the optical flow aggregated based on the emotion class. The images showcase the different characteristics of different emotions. Top: The three channels from OF (V_x, V_y, ε). The movement is shown in red. Bottom: Only the optical strain channel ε is displayed for clarity. The movement in shown in green and yellow.*

Introduction

As opposed to the typical macro-expressions each of us is confronted every day, micro-expressions (MEs) have a significantly lower intensity and a quicker duration [17]. The motivation for studying micro-expression arises from the fact that they are involuntary, meaning that micro-expressions show a person's genuine feelings. The ability to see person's true feelings has tremendous applications in psychotherapy, medical applications, business negotiations, lie detecting, security and marketing research [17].

However, due to the characteristics of MEs (low intensity, rapidness and involuntary) the task is not easy. In fact, the task is even difficult for humans. A micro-expression training tool [17] was developed to teach people how to spot and recognize emotions, but even after the training the accuracy was a mere 50%. Due to the potential applications and the difficulty of the task for humans, there has been an increasing amount of works that try to solve the problem of recognizing micro-expressions automatically.

Previous works on ME recognition have mainly focused on modelling and architectures. A problem that has been completely neglected to the best of our knowledge is the reliability of the datasets—more precisely the reliability of the labels for the samples. The authors of the ME datasets [28, 2] have acknowledged the difficulty and ambiguity of the labelling process. In fact, the inter-coder variability of labelling the AUs (action units) is only around 80% [28, 2]. The labelling is ambiguous as the same set of AUs may correspond to different emotions [30]. Another reason is the subjectivity of emotions, the personal feelings of the subject may not correspond to the labels of the annotator.

To see the extent of ambiguities, we manually go through the datasets to observe if the datasets contain ambiguous data. We find that there are indeed many ambiguous samples, including possibly mislabelled samples within the datasets. These mislabelled samples are often referred to as noisy labels in the literature [6, 21].

Motivated by these findings, we propose to use noisy label methods from the literature in an attempt to solve the problem. However, we found that the methods presented in the literature of noisy label methods did not work as effectively as expected. We hypothesize that this is due to the methods being designed for vastly different datasets with injected label noise, whereas we have a real world dataset. A similar finding was done in [5], where the authors notice the differences between synthetic datasets and real-world datasets. Therefore, we propose our own methods that are more suitable for ME data, but also potentially for similar datasets with the characteristics of a small number of samples and ambiguous data (as opposed to easily identifiable mislabelled

samples).

In this paper, we perform a qualitative analysis of ME data and develop noisy label methods for the potentially mislabelled samples. We conduct extensive experiments using multiple different noisy label methods and compare our developed methods to the state-of-the-art results in ME recognition.

Related Work

A Micro-expression analysis system can be divided into two parts. Firstly, the objective is to *spot* the occurring micro-expression. The output of spotting should be the onset and offset frame positions in which the ME is occurring. Secondly, after obtaining the sequence in which the ME is occurring, the task is to *recognize* the emotion with its corresponding category. In this paper, we only consider the latter task of recognizing the emotions, due to the complexity of the task. We will also look at the noisy label problem and the methods developed in an attempt to solve the problem from literature.

Micro-expression recognition methods

Previous work on ME recognition has been mainly in two categories: traditional methods and deep learning methods. The traditional methods refer to feature extraction by hand and they can be further split into two categories, appearance features and movement features. Many of the appearance-based methods are based on LBP (Local Binary Pattern). One of the most common benchmarks is the LBP-TOP (LBP on Three Orthogonal Planes) [31]. LBP based methods have further been explored by LBP-SIP (LBP with Six Intersection Points) [25], LBP-MOP (LBP with Mean Orthogonal Planes) [24] and ELBPTOP (Extended LBP-TOP) [4]. These methods focus on the pixel intensities, while movement based methods rely on the optical flow (OF). OF calculates the difference between two frames to find the movement between them. Methods using this strategy are HOOF (Histogram of Oriented Optical Flows) [1], MDMO (Main Directional Mean Optical Flow) [15], MDMOSparse [14] and Bi-WOOF [11, 8]. The deep learning methods instead use an automatic technique to extract the features. Methods from this section include Off-ApexNet [3], STSTNet [9] and NMER [13]. The deep learning methods have only recently become the state-of-the-art methods, due to the lack of data in ME datasets.

Noisy labels

Noisy labels refer to samples with incorrect labels. There are two main categories and common reasons for the mislabelled samples. 1) Massive datasets that have been generated without the supervision of humans. An example of this is WebData that is created by crawling images from the internet and labelling them based on the text around the image [21]. 2) Datasets with ambiguous samples. These are often smaller datasets and have been annotated by multiple humans, but due to the innate difficulty and ambiguity of the samples, there may be mistakes. Examples include medical datasets and ME datasets.

We formally define the noisy label problem here. Let $\mathscr{X} \subseteq \mathbb{R}^d$ be the space of inputs and the space $\mathscr{Y} = \{1,\dots,c\}$ be the label space, where d is the dimension of the inputs and c is the number of classes. In a typical case, we hope for the training set to consist of clean tuples of $(\mathbf{x}, y) \in (\mathscr{X}, \mathscr{Y})$, but in a noisy label case we have $(\mathbf{x}, \tilde{y}) \in (\mathscr{X}, \tilde{\mathscr{Y}})$, where $\tilde{\mathscr{Y}}$ is the set of noisy labels.

Table 1. Distributions of emotion classes for MEGC2019

Emotion class	Positive	Negative	Surprise	Total
SMIC	51	70	43	164
CASME II	32	88	25	145
SAMM	26	92	15	133
Combined	109	250	83	442

The task is to use the noisy set $(\mathscr{X}, \tilde{\mathscr{Y}})$ to learn the dataset as well as possible.

Noisy labels in micro-expressions

The noisy labels in micro-expressions may be caused by several possibilities. The labels are obtained from a convex combination of the following: 1) the subjects' own feelings, 2) the emotion from the eliciting video and 3) the annotator's subjective opinion. Any of these options are subject to mistakes. For example, different subjects may respond differently to a scary video—some find it scary but others just disgusting. In addition, the annotator may think of the emotion as something different, giving us a total of three different labels from each source. Further details on the ambiguity of the samples and noisy labels in micro-expressions can be found from [22].

Small-loss trick

A crucial finding that is commonly used throughout the different noisy label methods, named as the *small-loss* trick by [21]. The loss of a single sample is determined by the DNNs prediction. For example, the frequently used categorical cross-entropy $-\sum_{n\in\mathscr{N}} y_n \log(\hat{y}_n)$ measures the difference between two distributions, where $\mathscr{N}$ is the set of possible classes. If the distribution of the predicted label $\hat{y}$ is similar to that of the real label y, the loss will be small. If the distributions are different, then the loss will be high. For representative and unambiguous clean samples we would expect the loss to be small at the end of the training. For difficult clean samples, the loss may be high as the network is not able to fully match the distributions. For samples with noisy labels, we expect the loss to be high, as the network is predicting a distribution that does match the real label's distribution.

Noisy label methods

The noisy label methods can be roughly split into six different categories: loss functions, label cleaning, label refurbishment, transition matrices, loss reweighting and training procedures. The small-loss trick is utilized by q-percentile [6], which sorts the losses and discards $q\%$ of the samples with the highest losses. Generalized cross-entropy [29] uses a convex combination of ℓ_1 loss and the cross-entropy loss, as the ℓ_1 loss is able to find samples with high loss values, while cross-entropy keeps the training stable. T-revision [26] initially estimates the transition matrix $\mathbf{T}$ between the real labels y and the noisy labels $\tilde{y}$, using the predictions from the used network and the matrix is later revised by adding a slack variable to the initial estimation. Meta-Weight-Net [19] uses meta-learning to learn the weighting function of loss values, as opposed to manually selecting it like focal loss or self-paced learning. Manifold mixup [23] is a general regularizer that has also been used for noisy label learning. It creates new samples by a convex combination of samples' hidden layers and their labels.

A look at the data

This section provides a qualitative analysis of the ME data, where we will look at the the OF (optical flow) between the onset and the apex frame from the samples in the MEGC2019 [18] dataset. MEGC2019 is a composite dataset consisting of SMIC [7], CASME II [28] and SAMM [2]. The reason for combining the datasets is the sheer lack of samples, which can be seen from Table 1. Each sample consists of three channels: the horizontal component of OF, the vertical components of OF and the optical strain denoted by the triple (V_x, V_y, ε). We observe the OF domain as spotting and recognizing emotions from the original RGB videos is too difficult. Most recent works also use the OF as their input, as methods with RGB video input have not been nearly as effective as OF.

Figure 1 shows the mean samples of each emotion class. The *surprise* emotion has mainly movements on the forehead and eyebrows. The *positive* emotion mainly has movement on the left (from the participant) cheek. By looking at the optical strain, the movement seems to be on both cheeks and the mouth area. The *negative* emotion does not seem to have any distinct movements, there are some movements around the eyebrows, but also near the mouth. We believe this is due to the aggregated classes, as the MEGC2019 *negative* contains multiple other subclasses. The eyes are highlighted on all classes due to blinking. We will use these distinct movements of each class to search for any inconsistencies in the dataset.

Figure 2 shows the first 12 samples of MEGC2019. We can immediately observe that many of the samples contain noise at some level. An interesting discovery can be made from samples eight, nine, ten and eleven. All of these samples look similar, but one of them is labelled as *positive* while the others are labelled as *surprise*. Sample number eight also contains some movements on their cheeks which may have been the reason for the label *positive*, but so does sample number ten and it has not been labelled as *positive*. This is a typical example of an ambiguous sample, where there could even be two correct labels, as the sample contains two distinct movements for two different emotions. However, confirming that this sample has a noisy label is difficult as we do not have an expert to confirm the finding and since this is only the apex of the OF, many more things could be happening in the other frames in the original domain. Nevertheless for the model performing the classification this sample will most likely be classified as *surprise* due to the distinct movements in the forehead. We find more similar samples by going through the dataset and hypothesize that these are samples that have been labelled incorrectly.

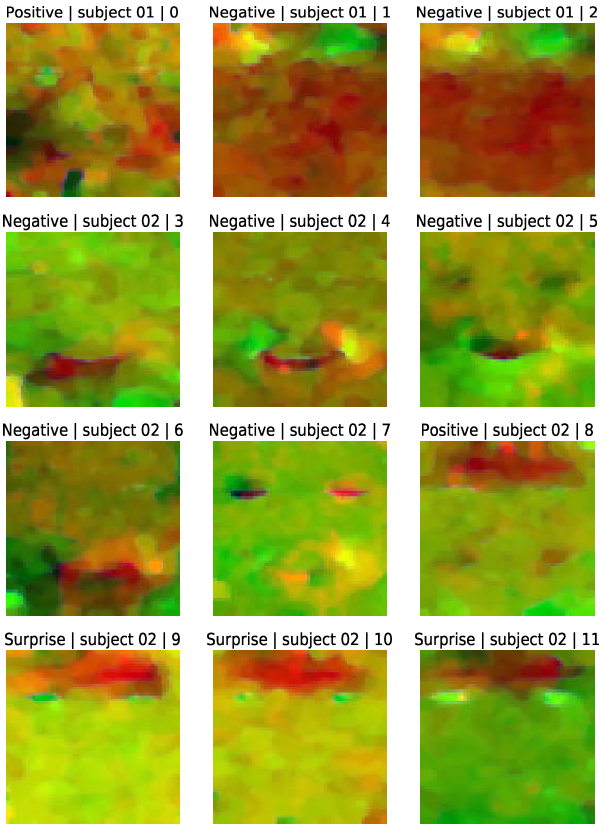


Figure 2. *First 12 samples of MEGC2019. The title of each image consists of* ***the emotion class*** | ***the subject number*** | ***the sample number****.*

Methodology

In this section we will introduce our developed methods initial data cleaning (IDC) and iterative label correction (ILC) to deal with the noisy labels. In addition we provide a neural network architecture based on the related work.

Initial data cleaning (IDC)

It was found in [6] that only using clean data (10% of the full data) can lead to a better performance than using the whole dataset, including the noisy samples. Inspired by this, we manually go through the dataset to find clean samples similarly to the previous section. From the 442 samples of MEGC2019 we find a total of 240 clean samples and 202 samples that are noisy, have a potentially incorrect label, ambiguous or do not fit the typical characteristics of MEs found in the previous section.

However, after experimentation, we found that the performance had decreased when only training with the clean samples. A finding in [21] points out that data cleaning methods may be cleaning too many samples, discarding samples that are crucial for the training. In the work [12] the authors find that regularizing the network early significantly prevents the network from memorizing the noisy labels in the later stages of the training. Inspired by this we propose a warm-up period during which the network is only trained with clean labels for some duration of epochs, hence the data cleaning is only done *initially*. After the warm-up period, the network has access to all of the data.

Loss thresholding with moments (LTM)

We introduce loss thresholding with moments here as it is used as a sub method in ILC. We use an alternative way of performing the q-percentile also based on the small-loss trick. One of the downsides of q-percentile is the need for a warm-up period as the small-loss trick does not apply at the beginning of the training when the losses are essentially random. In [6] the authors propose to store the mean μ and standard deviation σ of the losses of the

most recent 100 training samples. Then they threshold the values if the loss value is higher than $\mu + 1.5\sigma$. We use the same idea but set the coefficient to be a hyperparameter α, thus the threshold value is then given by

$$t = \mu + \alpha\sigma. \tag{1}$$

The hyperparameter α behaves similarly to q and is required as different datasets have different levels of noise. The number of training samples from which the mean and standard deviation are calculated is set to be equal to the number of samples in a batch. This allows us to perform an update based on the most recent loss values and have enough samples to calculate the moments. In addition, by calculating the moments from the batch samples, we can avoid more complex implementations. The value may have to be adjusted depending on the size of the dataset and if the ratio of noisy labels is small. We refer to the method as loss thresholding with moments (LTM) as we use the first and second moments of the distribution to formulate the threshold value.

The set of samples with clean labels

$$\mathscr{C} = \{(\mathbf{x}, y) \in (\mathscr{X}, \mathscr{Y}) \mid \mathscr{L}(f(\mathbf{x};\theta), y) < t\} \tag{2}$$

is then obtained by thresholding the loss values obtained from an arbitrary loss function $\mathscr{L}$ of each sample, where the network f gives the prediction. Then, the samples with high loss values are ignored when updating the parameters of the network θ and only the set of clean samples is used in the update. The benefit of using LTM over q-percentile is that there is no need for a warm-up period at the start of the training. As the threshold value t is given as a function of the moments of the loss distribution, the number of discarded samples is adaptive and there is no need for a warm-up period.

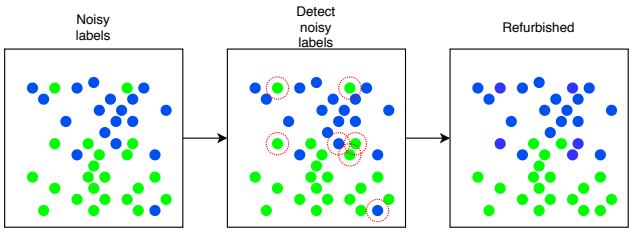


Figure 3. *The figure depicts Iterative label correction. (Left) We start with a set of noisy labels. (Middle) We detect the noisy labels similarly to LTM. (Right) The samples that are detected as noisy labels are refurbished by the network's most recent prediction and we are left with the clean set $\mathscr{C}$ and the corrected set $\mathscr{R}$ given by Equation (3). By correcting the labels we are left with the same amount of samples that we started with.*

Iterative label correction (ILC)

An issue with LTM, and overall with methods discarding samples, is that the discarded samples may be important for the training in small datasets. We can include the detected samples with noisy labels by refurbishing the noisy label with a corrected one as shown in Figure 3. Our method is similar to SELFIE [20], but instead of using q-percentile we apply the LTM for finding the noisy labels. The refurbished label is given by the current prediction of the network instead of a uncertainty condition employed by SELFIE. ILC only corrects the labels of samples that have been detected as high loss samples, while SELFIE also includes some of the clean samples.

The set of samples with corrected labels

$$\mathscr{R} = \{(\mathbf{x}, \hat{y}) \mid (\mathbf{x}, y) \in \mathscr{C}^c,\ \hat{y} = f(\mathbf{x};\theta)\} \tag{3}$$

is given by the predictions of the network for samples that were not found to be clean, *i.e.*, the complement of $\mathscr{C}$. The parameters θ are then updated using the set $\mathscr{C} \cup \mathscr{R}$.

The correction of labels can be risky however. If the network has not learned the dataset correctly, it is not able to distinguish between the samples and the corrected labels may be incorrect. Giving the high loss samples incorrect labels could lead to an increase in the number of noisy labels.

Shallow Single Stream Network

We introduce SSSNet (Shallow Single Stream Network) that is motivated by Off-ApexNet [10], STSTNet [9] and from the findings in [27]. One of the problems with Off-ApexNet and STSTNet is that they have a separate stream for each of the input channels (V_x, V_y, ε). This does not allow the network to combine the learned information from each of the channels until the fusion of the features. We simplify the network by only using a *single* stream that contains all input channels. The structure of the network can be seen in Figure 4. We refer to SSSNet24 as the model in which the number of filters in the second convolutional layer is changed to 24.

Experiments

This section presents the experimental settings and the results of our experiments. We first start by comparing different noisy label methods, next we analyze the results and the effectiveness of the methods and lastly compare our methods to the state of the arts.

Evaluation methods

The evaluation is performed using the LOSO (leave-one-subject-out) protocol. In LOSO the data is split into training and testing data such that the testing set only contains samples from a single subject and the training set contains the rest. This is done as emotions are highly subject dependent. The performance is measured by the unweighted

$$F1 = \frac{1}{C}\sum_{c=1}^{C}\frac{2TP_c}{2TP_c + FP_c + FN_c} \tag{4}$$

and the

$$UAR = \frac{1}{C}\sum_{c=1}^{C}\frac{TP_c}{N_c}, \tag{5}$$

where C is the number of classes and N is the number of samples, as the classes are imbalanced.

Comparison with noisy label methods

Table 2 showcases the results from different noisy label methods. SSSNet24 is used for the baseline, as well as the backbone for the other methods. In the middle part of the table we showcase the results using methods from the literature. All of

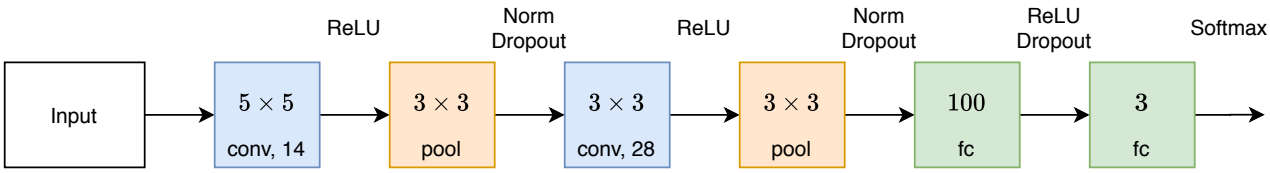


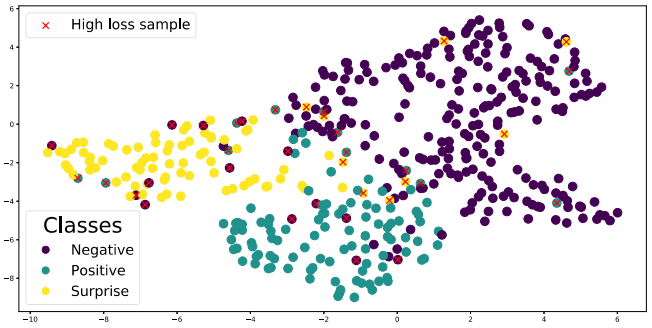
Figure 4. *Network architecture of SSSNet. The architecture consists of two convolutional layers, two pooling layers and two fully connected layers. Batch normalization and dropout are used to regularize the model.*

Table 2. $F1$**-*scores* from different noisy label methods. The baseline and backbone for all the methods is SSSNet24**

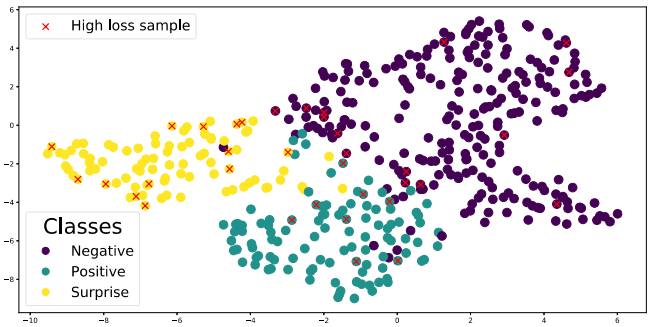
Model	$F1$			
	MEGC2019	SMIC	CASME II	SAMM
Baseline	0.7415	0.7005	0.8739	0.6302
q-percentile	0.7489	0.6792	0.8844	0.6601
Man. Mixup	0.7472	0.6901	0.8686	0.6639
Gen. CE	0.7507	**0.7103**	0.8796	0.6341
T-revision	0.7322	0.6574	0.8389	0.6699
Meta-W-Net	0.7527	0.6861	0.8442	**0.7008**
LTM	0.7553	0.6895	0.8838	0.6738
ILC	0.7639	0.6919	0.8995	0.6829
IDC	**0.7707**	0.6979	**0.8996**	0.6919

the methods are able to outperform the baseline for MEGC2019 except for T-revision. We hypothesize that since the matrix transition methods model the transition of classes, it is better suited for methods with a high number of noisy labels and larger datasets. In addition, the transition matrix only mitigates the effects of noisy labels, but we found that the data also contains samples with noise in the data itself, which the other methods are also able to detect. The other methods are able to increase the performance of the baseline, but quite moderately. In the bottom section of the table, we have the proposed methods. These methods were found to better perform for ME recognition, as they are specifically designed for the task. The initial data cleaning method is able to increase the baseline by 4%, while the loss thresholding with moments and iterative label cleaning fall a bit short of that.

The success of multiple different noisy label methods indicates the presence of noisy labels in the dataset. The relative incremental increases in performance can be explained as some of the methods are designed for larger datasets with higher amounts of noisy labels. In addition, a recent work from [5] discusses the differences between real-world label noise and synthetically generated label noise and finds the distributions to be relatively different. And since most of the noisy label methods in the literature have been developed using synthetically generated noise, they may fall short with real world data. Probably the biggest reason as to why the improvements are only incremental compared to what the noisy label methods are able to achieve in their own benchmarks, is that we do not have access to clean validation data. Due to the constraints of the LOSO protocol, all samples have to be tested. This means that even if we were able to perfectly detect all noisy samples, the improvement would be marginal as the testing data still contains noisy labels. However, the improvements achieved here are still a sign that the methods are able to better generalize and do not overfit to noisy labels as heavily.



(a) A UMAP projection to two dimensions from the last hidden layer. Each sample has been colored by their respective class. The red crosses mark samples that exceed the threshold and are thus determined to be high loss samples.



(b) Similar to the figure (a), but the high loss samples have been refurbished using ILC.

Figure 5. *UMAP projections from the last hidden layer of SSSNet24.*

Figure 5a shows a projection from the last hidden layer of SSSNet24 to two dimensions using UMAP (uniform manifold approximation and projection) [16]. The classes cluster relatively well and the class borders can be roughly drawn. Some samples seem to be in the wrong clusters, which we have been able to detect using loss thresholding with moments. Unfortunately, not all samples that seem to be in the wrong clusters have been detected. In addition, samples with a correct label may also have

Table 3. Comparison to the state-of-the-art methods

Model	MEGC2019		SMIC		CASME II		SAMM	
	UAR	$F1$	UAR	$F1$	UAR	$F1$	UAR	$F1$
LBP-TOP [31]	0.5785	0.5882	0.5280	0.2000	0.7429	0.7026	0.4102	0.3954
MDMO [15]	0.5782	0.5881	0.5511	0.5587	0.7925	0.8014	0.3073	0.3065
Off-ApexNet [10]	0.7164	0.7176	0.6972	0.7039	0.8094	0.8159	0.6172	0.6126
STSTNet [9]	0.7125	0.7095	0.6726	0.6618	0.8132	0.8325	0.6257	0.6176
NMER [13]	0.5936	0.5936	0.5555	0.5607	0.6929	0.7624	0.4894	0.6389
RCN-A [27]	0.7138	0.7168	0.6619	0.6590	0.7894	0.8109	0.6531	0.6547
SSSNet24	0.7505	0.7415	0.7071	**0.7005**	0.8739	0.8716	0.6417	0.6302
SSSNet24 + LTM	0.7647	0.7553	0.7009	0.6895	0.8814	0.8838	0.6848	0.6738
SSSNet24 + ILC	0.7729	0.7639	0.6979	0.6919	0.9051	0.8995	0.6919	0.6829
SSSNet24 + IDC	**0.7794**	**0.7707**	**0.7090**	0.6979	**0.9060**	**0.8996**	**0.6990**	**0.6919**

been marked as high loss samples as can be seen with samples marked at the classification border of *negative* and *positive*.

Figure 5b shows the same projection, but the labels from the samples that were detected as high loss samples have now been corrected with ILC. Here we can see that essentially all of the samples were corrected to a label that best represents their neighboring points. Once more, some arguments can be made about the samples in the classification border of *negative* and *positive*.

Comparison to state of the arts

We compare our methods to the state-of-the-art methods from the literature in Table 3. At the top we have the two traditional methods LBP-TOP and MDMO. Both of the methods achieve similar results at around 0.58 $F1$. In the middle we have the current state-of-the-art methods for ME recognition that have been evaluated using the MEGC2019 dataset. SSSNet24 with the proposed methods are presented in the bottom of the table. The IDC method is able to achieve the state of the art for ME recognition of 0.77 in the $F1$-*score*. Both the ILC and IDC are very close to breaking the 0.90 mark for $F1$ in the CASME II dataset. Significant increases can be seen in both CASME II and SAMM compared to the previous state-of-the-art methods.

Conclusions

We have showcased the effectiveness of using noisy label methods for micro-expression recognition, although previous ME recognition methods have ignored the ambiguity of the data. We started off by observing the labelling process of the datasets and by looking at individual samples, in order to better understand the problem of noisy labels. We proposed two new methods: initial data cleaning and iterative label correction, to address the issue of noisy labels. In initial data cleaning, we manually go through the dataset to find clean samples and only use the clean samples in the initial stages of the training. Iterative label correction finds noisy samples using loss thresholding with moments and then corrects the noisy labels using the network's predictions. We perform experiments using noisy label methods for micro-expression recognition and find that nearly all of the methods are able to increase the performance, indicating the existence of noisy samples in micro-expressions datasets. Besides, we achieve the state of the art for MEGC2019 with an $F1$-*score* of 0.77 by using the initial data cleaning method showing its effectiveness. As a future work, we hope to study the relationship between subjective facial emotion perception and the proposed methods for finding samples with noisy labels.

Acknowledgements

This work was supported by the Academy of Finland for ICT 2023 project (grant 328115), project MiGA (grant 316765), and Infotech Oulu. As well, the authors wish to acknowledge CSC – IT Center for Science, Finland, for computational resources.

References

[1] Chaudhry, R., Ravichandran, A., Hager, G., and Vidal, R. Histograms of oriented optical flow and binet-cauchy kernels on nonlinear dynamical systems for the recognition of human actions. In *2009 IEEE Conference on Computer Vision and Pattern Recognition* (June 2009), pp. 1932–1939.

[2] Davison, A. K., Lansley, C., Costen, N., Tan, K., and Yap, M. H. Samm: A spontaneous micro-facial movement dataset. *IEEE Transactions on Affective Computing 9*, 1 (Jan 2018), 116–129.

[3] Gan, Y., Liong, S.-T., Yau, W.-C., Huang, Y.-C., and Tan, L.-K. Off-apexnet on micro-expression recognition system. *Signal Processing: Image Communication 74* (2019), 129–139.

[4] Guo, C., Liang, J., Zhan, G., Liu, Z., Pietikäinen, M., and Liu, L. Extended Local Binary Patterns for Efficient and Robust Spontaneous Facial Micro-Expression Recognition. *arXiv e-prints* (Jul 2019), arXiv:1907.09160.

[5] Jiang, L., Huang, D., Liu, M., and Yang, W. Beyond synthetic noise: Deep learning on controlled noisy labels, 2020.

[6] Karimi, D., Dou, H., Warfield, S. K., and Gholipour, A. Deep learning with noisy labels: exploring techniques and remedies in medical image analysis, 2019.

[7] Li, X., Pfister, T., Huang, X., Zhao, G., and Pietikäinen, M. A spontaneous micro-expression database: Inducement, collection and baseline. In *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)* (April 2013), pp. 1–6.

[8] Liong, S., and Wong, K. Micro-expression recognition using apex frame with phase information. In *2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)* (Dec 2017), pp. 534–537.

[9] Liong, S.-T., Gan, Y. S., See, J., Khor, H.-Q., and Huang, Y.-C. Shallow triple stream three-dimensional cnn (ststnet) for micro-expression recognition, May 2019.

[10] Liong, S.-T., Gan, Y. S., Yau, W.-C., Huang, Y.-C., and

KEN, T. L. Off-apexnet on micro-expression recognition system, 2018.

[11] LIONG, S.-T., SEE, J., WONG, K., AND PHAN, R. C.-W. Less is more: Micro-expression recognition from video using apex frame. *Signal Processing: Image Communication 62* (2018), 82 – 92.

[12] LIU, S., NILES-WEED, J., RAZAVIAN, N., AND FERNANDEZ-GRANDA, C. Early-learning regularization prevents memorization of noisy labels, 2020.

[13] LIU, Y., DU, H., ZHENG, L., AND GEDEON, T. A neural micro-expression recognizer. In *2019 14th IEEE international conference on automatic face & gesture recognition (FG 2019)* (2019), IEEE, pp. 1–4.

[14] LIU, Y., LI, B., AND LAI, Y. Sparse mdmo: Learning a discriminative feature for spontaneous micro-expression recognition. *IEEE Transactions on Affective Computing* (2018), 1–1.

[15] LIU, Y., ZHANG, J., YAN, W., WANG, S., ZHAO, G., AND FU, X. A main directional mean optical flow feature for spontaneous micro-expression recognition. *IEEE Transactions on Affective Computing 7*, 4 (Oct 2016), 299–310.

[16] MCINNES, L., HEALY, J., AND MELVILLE, J. Umap: Uniform manifold approximation and projection for dimension reduction, 2018.

[17] OH, Y., SEE, J., NGO, A. C. L., PHAN, R. C., AND BASKARAN, V. M. A survey of automatic facial micro-expression analysis: Databases, methods and challenges. *CoRR abs/1806.05781* (2018).

[18] SEE, J., YAP, M. H., LI, J., HONG, X., AND WANG, S.-J. Megc 2019 – the second facial micro-expressions grand challenge. pp. 1–5.

[19] SHU, J., XIE, Q., YI, L., ZHAO, Q., ZHOU, S., XU, Z., AND MENG, D. Meta-weight-net: Learning an explicit mapping for sample weighting, 2019.

[20] SONG, H., KIM, M., AND LEE, J.-G. Selfie: Refurbishing unclean samples for robust deep learning. In *International Conference on Machine Learning* (2019), pp. 5907–5915.

[21] SONG, H., KIM, M., PARK, D., AND LEE, J.-G. Learning from noisy labels with deep neural networks: A survey, 2020.

[22] VARANKA, T. Facial micro-expression recognition with noisy labels. Master's thesis.

[23] VERMA, V., LAMB, A., BECKHAM, C., NAJAFI, A., MITLIAGKAS, I., COURVILLE, A., LOPEZ-PAZ, D., AND BENGIO, Y. Manifold mixup: Better representations by interpolating hidden states, 2018.

[24] WANG, Y., SEE, J., PHAN, R., AND OH, Y.-H. Efficient spatio-temporal local binary patterns for spontaneous facial micro-expression recognition. *PloS one 10* (05 2015), e0124674.

[25] WANG, Y., SEE, J., PHAN, R. C.-W., AND OH, Y.-H. Lbp with six intersection points: Reducing redundant information in lbp-top for micro-expression recognition. In *Computer Vision – ACCV 2014* (Cham, 2015), D. Cremers, I. Reid, H. Saito, and M.-H. Yang, Eds., Springer International Publishing.

[26] XIA, X., LIU, T., WANG, N., HAN, B., GONG, C., NIU, G., AND SUGIYAMA, M. Are anchor points really indispensable in label-noise learning? In *Advances in Neural Information Processing Systems* (2019), pp. 6838–6849.

[27] XIA, Z., PENG, W., KHOR, H.-Q., FENG, X., AND ZHAO, G. Revealing the invisible with model and data shrinking for composite-database micro-expression recognition, 2020.

[28] YAN, W.-J., LI, X., WANG, S.-J., ZHAO, G., LIU, Y.-J., CHEN, Y.-H., AND FU, X. Casme ii: An improved spontaneous micro-expression database and the baseline evaluation. *PLOS ONE 9*, 1 (01 2014), 1–8.

[29] ZHANG, Z., AND SABUNCU, M. R. Generalized cross entropy loss for training deep neural networks with noisy labels, 2018.

[30] ZHAO, G., AND LI, X. Automatic micro-expression analysis: Open challenges. *Frontiers in Psychology 10* (2019), 1833.

[31] ZHAO, G., AND PIETIKAINEN, M. Dynamic texture recognition using local binary patterns with an application to facial expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence 29*, 6 (June 2007), 915–928.

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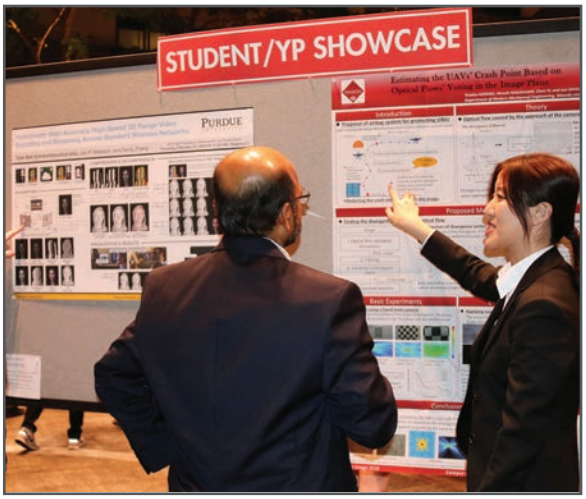

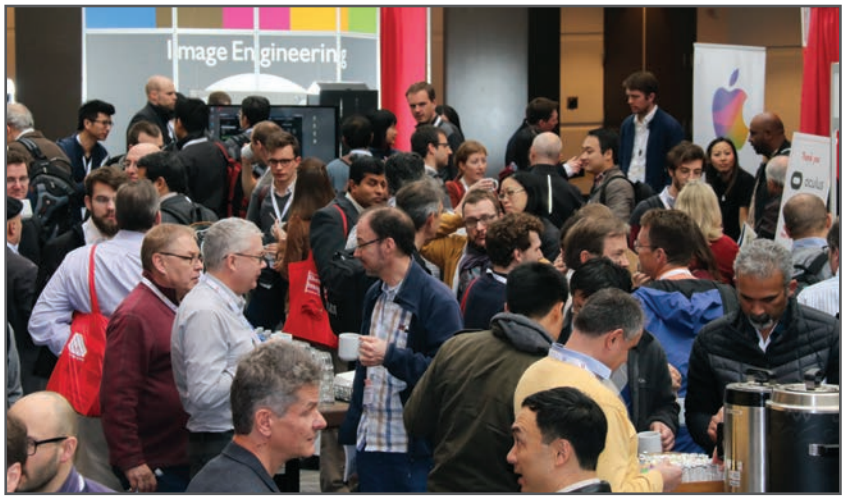

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