TEMPORAL COHERENT TEST-TIME OPTIMIZATION FOR ROBUST VIDEO CLASSIFICATION

Anonymous authors
Paper under double-blind review

ABSTRACT

Deep neural networks are likely to fail when the test data is corrupted in real-world deployment (e.g., blur, weather, etc.). Test-time optimization is an effective way that adapts models to generalize to corrupted data during testing, which has been shown in the image domain. However, the techniques for improving video classification corruption robustness remain few. In this work, we propose a **Te**mporal **Co**herent Test-time Optimization framework (TeCo) to utilize spatio-temporal information in test-time optimization for robust video classification. To exploit information in video with self-supervised learning, TeCo minimizes the entropy of the prediction based on the global content from video clips. Meanwhile, it also feeds local content to regularize the temporal coherence at the feature level. TeCo retains the generalization ability of various video classification models and achieves significant improvements in corruption robustness across Mini Kinetics-C and Mini SSV2-C. Furthermore, TeCo sets a new baseline in video classification corruption robustness via test-time optimization.

1 INTRODUCTION

Deep neural networks have achieved tremendous success in many computer vision tasks when the training and test data are identically and independently distributed (i.i.d). However, the mismatch between them is common when the model is deployed in the real world. For example, weather changes like rain and fog, and data pre-processing like saturate adjustment and compression can corrupt the test data. Many works show that the common corruptions arising in nature can degrade the performance of models at test time significantly (Hendrycks & Dietterich, 2019; Yi et al., 2021; Kar et al., 2022; Geirhos et al., 2018). In video classification, Yi et al. (2021) demonstrates the vulnerability of models against corruptions like noise, blur, and weather variations.

Various techniques have been proposed to improve the robustness of models against common corruptions (a.k.a.corruption robustness). The most popular direction is increasing the diversity of input training data via data augmentations and applying regularization at training time (Zheng et al., 2016; Wang et al., 2021b; Hendrycks et al., 2020; Rusak et al., 2020). It trains one model and evaluates on all types of corruption. However, the training data is often unavailable because of privacy concerns and policy constraints, making it more challenging to deploy models in the real world. In this work, we focus on the direction of test-time optimization. Under such a scheme, the parameters of one model will be optimized by one type of corrupted test data specifically. Test-time optimization updates the model to fit into the deployment environment at test time, without access to training data. There are several test-time optimization techniques emerging in image-based tasks (Wang et al., 2021a; Schneider et al., 2020; Liang et al., 2020; Sun et al., 2020). However, we find these techniques are not able to generalize to video-based corruption robustness tasks well from empirical analysis. We hypothesize the gap between image and video-based tasks comes from several aspects. Firstly, the corruptions in the video can change temporal information, which requires the model to be both generalizable and robust (Yi et al., 2021). Hence, improving model robustness against the corruptions in video like bit error, and frame rate conversion is more challenging. Secondly, video input data has a different format from image data. For example, video data has a much larger size than image data. It is impractical to use a similar batch size as image-based tasks (e.g., batch size of 256 in Tent (Wang et al., 2021a)), though the batch size is an important hyper-parameter in test-time optimization (Wang et al., 2021a; Schneider et al., 2020). Lastly, these techniques ignore the huge information hidden in the temporal dimension.

To improve the video classification model robustness against corruptions consistently, we propose a temporal coherent test-time optimization framework **TeCo**. TeCo is a test-time optimization technique with two self-supervised objectives. We propose to build our method upon the test-time optimization which updates all the parameters in shallow layers and only normalization layers in the deep layers. It can benefit from both training and test data, and such an optimization strategy remains part of model parameters and statistics obtained at training time and updates the unfrozen parameters with test information. Besides, we utilize global and local spatio-temporal information for self-supervision. We use uniform sampling to ensure global information in input video data and optimize the model parameters via entropy minimization. By dense sampling, we extract another local stream that has a smaller time gap between consecutive frames. Due to the smooth and continuous nature of adjacent frames in the video (Li & DiCarlo, 2008; Wood & Wood, 2016), we apply a temporal coherence regularization as a self-supervisor in test-time optimization on the local pathway. As such, our proposed technique enables the model to learn more invariant features against corruption. As a result, TeCo achieves promising robustness improvement on two large-scale video corruption robustness datasets, Mini Kinetics-C and Mini SSV2-C. Its performance is superior across various video classification backbones. TeCo increases 8% and 5.4% average accuracy across backbones on Mini Kinetics-C and Mini SSV2-C, which is better than the baseline methods Tent (2.1% and 1.1%) and SHOT (2.4% and 2.6%). Additionally, We show that TeCo can guarantee the smoothness between consequent frames at the feature level, which indicates the effectiveness of temporal coherence regularization.

We summarize our contributions as follows:

- To the best of our knowledge, we make the first attempt to study the test-time optimization techniques for video classification corruption robustness across datasets and model architectures.
- We propose a novel test-time optimization framework TeCo for video classification, which utilizes spatio-temporal information in training and test data to improve corruption robustness.
- For video corruption robustness, TeCo outperforms other baseline test-time optimization techniques significantly and consistently.

2 Related Works

2.1 Problem Setting

Corruption Robustness. Deep neural networks are vulnerable to common corruptions generated in real-world deployment (Geirhos et al., 2017; Hendrycks & Dietterich, 2019). Hendrycks & Dietterich (2019) firstly propose ImageNet-C to benchmark the common corruption robustness of deep learning models. It assumes the tested model has no prior knowledge of the corruption arising during test time. The model is trained with clean data while tested on corrupted data. Under such a setting, we are able to estimate the overall robustness of models against corruption. In the following, benchmark studies and techniques across various computer vision tasks are booming (Kar et al., 2022; Michaelis et al., 2019; Kamann & Rother, 2020). These studies on corruption robustness bridge the gap between research in well-setup lab environments and deployment in the field. Recently there emerge studies on corruption robustness in video classification (Yi et al., 2021; Wu & Kwiatkowska, 2020). In this work, we tap the potential of spatio-temporal information in video data and improve the corruption robustness of video classification models during testing.

Video Classification. Recently, with the introduction of a number of large-scale video datasets such as Kinetics (Carreira & Zisserman, 2017), Something-Something V2 (SSV2) (Goyal et al., 2017), and Sports1M (Karpathy et al., 2014), video classification has attracted increasing attention. Most existing video classification works mainly focus on two perspectives: improving accuracy (Simonyan & Zisserman, 2014; Wang et al., 2016; Carreira & Zisserman, 2017; Hara et al., 2017; Xie et al., 2018; Bertasius et al., 2021; Li et al., 2022) and model efficiency (Feichtenhofer et al., 2019; Lin et al., 2019; Feichtenhofer, 2020; Kondratyuk et al., 2021; Wang et al., 2021c). However, as mentioned above, techniques for improving video classification corruption robustness remain few. In this paper, we focus on the optimization of video corruption robustness and conduct experiments

on Mini Kinetics-C and Mini SSV2-C datasets. The Kinetics dataset relies on spatial semantic information for video classification, while SSV2 contains more temporal information. It enables us to evaluate the effectiveness of our proposed optimization method on these two different types of video data.

2.2 TEST-TIME OPTIMIZATION

Optimizing the model with unlabeled test data has been used in many machine learning tasks (Shu et al., 2022; Huang et al., 2020; Shocher et al., 2018; Azimi et al., 2022; Niu et al., 2022; Wang et al., 2022). These methods only require the pretrained model and test data for optimization in the inference. Test-Time Training (TTT) (Sun et al., 2020) and TTT++ (Liu et al., 2021) update models at test-time, but they jointly optimize the supervised loss and the self-supervised auxiliary loss in training. Though these methods demonstrate promising improvement in image-based corruption robustness, there is little progress made in video-based test-time optimization. We make the first attempt to utilize the temporal information for model robustness under the test-time optimization setting.

2.3 TEMPORAL COHERENCE IN VIDEO

The concept of temporal coherence makes an assumption that adjacent frames in video data have semantically similar information (Goroshin et al., 2015). The assumption is based on the phenomenon that the visual world is smoothly varying and continuous. The stability of the visual world in the temporal dimension is significant for many studies in biological vision (Li & DiCarlo, 2008; Wood, 2016; Wood & Wood, 2016). With the assumption, the invariance between neighboring frames in the video can provide self-supervision for many computer vision tasks (Jayaraman & Grauman, 2015; Wiskott & Sejnowski, 2002; Dwibedi et al., 2019; Wang et al., 2019). For example, Jayaraman & Grauman (2015) exploits motion signal in egocentric video to regularize image recognition task; Wang et al. (2019) utilizes the cycle consistency in time to learn visual temporal correspondence. In the corruption robustness problem, we use temporal coherence as a self-supervisor to regularize models to be more invariant against corruption.

3 METHOD

We propose an end-to-end training framework to improve the robustness of video classification models against corruption at test time. In such a framework, we optimize pre-trained deep learning models during the test time and minimize two objectives without label information. These two objectives correspond to two pathways. The first pathway uses a global stream as input and minimizes the entropy of prediction; the second pathway leverages a local stream as input and regularizes the temporal coherence among consecutive video frames. We integrate these two pathways and named our framework as **TeCo**. Figure 1 outlines our temporal coherent test-time optimization framework. The backbone in Figure 1 is initialized by a pre-trained model. Any deep video classification model pretrained under a supervised learning scheme can fit into it.

3.1 TEST-TIME OPTIMIZATION STRATEGY

Though BN (Schneider et al., 2020) and Tent (Wang et al., 2021a) achieve promising performance on image-based test-time optimization tasks, they have subtle enhancement on video data and sometimes degrade the robustness on corruptions in our empirical analysis. BN only adapts the mean and variance of normalization layers by test data partially, it limits the searching space of optimization. Tent removes the training time batch normalization statistics fully, while video classification tasks usually have smaller batch size. It can only capture sub-optimal statistics when just relying on test-time data.

We perform a simple but effective mechanism by grafting the advantage of these two classic techniques. Following (Schneider et al., 2020), we initialize mean $\mu = \alpha\mu_s + (1-\alpha)\mu_t$ and variance $\sigma^2 = \alpha\sigma_s^2 + (1-\alpha)\sigma_t^2$, where s stands for training, and t stands for testing. α is the hyper-parameter that controls the weights of training and test time statistics. At the same time, we update the affine

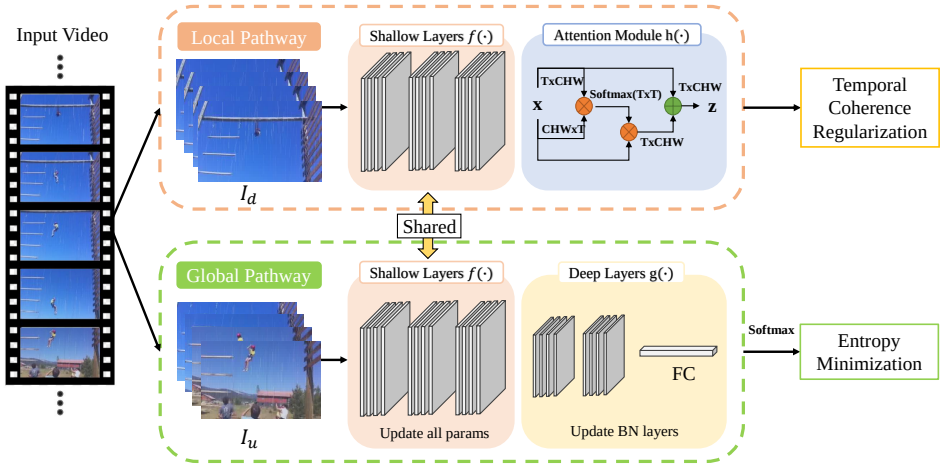

Figure 1: The proposed framework TeCo at the test-time optimization stage. TeCo consists of two pathways: the local pathway uses dense video stream I_d as input. It passes through the shallow layers f and attention module h to generate an attention-based feature map z. Then it applies temporal coherence regularization on the feature map. We update all the parameters in the shallow layers in this pathway; the global pathway uses a sparse video stream I_u, which captures the long-term information. TeCo minimizes the prediction entropy in the global pathway by updating all the parameters in the shallow layers and only normalization parameters in the deep layers.

transformation parameters in the normalization layers, which helps the model to utilize both training and test-time statistics after adaptation.

Apart from normalization layers, we also fine-tune other network parameters (e.g., Conv Layers) in the shallow layers. The shallow layers of robust models generate smoother feature tensors that are better aligned with human perception (Xie et al., 2019; Tsipras et al., 2018). They play the role of denoiser when encountering natural corruptions arising in input data. Inspired by this phenomenon, we update all the parameters in the shallow layers and only normalization layers in the deep layers. The separation is as shown in Figure 1. It gives more flexibility to the shallow layers while not interrupting the higher-level semantic information.

3.2 Global and Local Pathways

In the test-time optimization of TeCo, we use two pathways (i.e, global pathway and local pathway) and two objectives to optimize model. The global pathway uses uniform sampling to extract frames from the input video I_u. The uniform sampling splits the video into multiple clips with equal length. Then we randomly take one frame from each clip. As a result, the selected frames by uniform sampling can capture the global information effectively (Chen et al., 2021). In this pathway, we optimize the overall parameters of shallow layers and the transformation parameters in deep normalization layers by minimizing the entropy of prediction. The objective is $L_{ent} = H(Softmax(g(f(I_u)))$, where H is the Shannon entropy of prediction $\hat{y}$ with N classes: $H(\hat{y}) = -\sum_{n=1}^{N} p(\hat{y}_n) \log p(\hat{y}_n)$. It serves as the optimization of the global pathway.

The local pathway leverages dense sampling to take consecutive frames I_d, at a random location of the input video, which randomly chooses a location as the center of the sampled sequence. Compared to the large time gap in frames by uniform sampling, the time gap in the frames by dense sampling can be as low as one. In this pathway, the temporal coherence between frames is much stronger. Because the visual world is smoothly varying, the neighboring frames in video data will not change abruptly in the temporal dimension. When common corruptions interrupt the natural structure of video data, we apply a temporal-coherent regularization to the output feature of the shallow layer. The regularization can be achieved by enforcing the feature similarity in consecutive feature maps of corrupted data. We explicitly represent it with the loss function:

$$L_{coherence} = \sum_{t=1} ||x^t - x^{t-i}||_1. \tag{1}$$

We use l_1 distance to measure the similarity of feature tensors. x^t is the tensor at time t, which is the output after $f(I_d^t)$. i is the time gap between two neighboring tensors. Equation 1 encourages the layers to generate smoother features. Correspondingly, the feature extractor will be more invariant to the perturbation, corruption, and disruption in the input data. It leads to more robust video classification models.

3.3 Attentive Temporal Coherence Regularization

When we apply Equation 1 on feature tenors, we simply assume the frames are varying in a uniform speed because of the same weights along the time dimensions. However, the changes in neighboring frames have different scales in the real world. The example of bungee jumping in Figure 1 shows that the change is small at the beginning of the video because the background is fixed. It has only the blue sky and a jumping platform. When the person is reaching the ground, the background changes rapidly, and there are houses and other people appearing. Hence, we propose to assign different weights to different frames. To encourage temporal consistency in the static background, the slower changes in temporal dimension correspond to higher weights in regularization. The weights can be generated by an attention module h. In this work, we use the time dimension-only 1D non-local operation (Wang et al., 2018) to obtain the weights along the time dimension. Hence, the attentive temporal coherent regularization can be written as:

$$L_{att-co} = \sum_{t=1} ||h(f(I_d))^t - h(f(I_d))^{t-i}||_1, \tag{2}$$

where h is the attention module.

3.4 Overall Objective Function

To summarize, the global pathway uses I_u as input and entropy minimization as objective, and the local pathway leverages I_d as input and attentive temporal coherence regularization as objective. The overall objective function for TeCo can be represented as:

$$L = L_{ent}(I_u, f, g) + \beta L_{att-co}(I_d, f, h), \tag{3}$$

where $\beta > 0$ is a balancing hyper-parameter.

4 Experiments

We evaluate the corruption robustness of TeCo on Mini Kinetics-C and Mini SSV2-C. The mean performance on corruption is the main metric for robustness measurement. We also compare it with other baseline methods across architectures.

Dataset. Kinetics (Carreira & Zisserman, 2017) and Something-Something-V2 (SSV2) (Goyal et al., 2017) are two most popular large-scale datasets in video classification community . Kinetics is extracted from the Youtube website and it relies on spatial information for classification. It contains around 10K videos in the test dataset. As complementary, SSV2 is a first-view video dataset constructed systematically in the lab environment, which has more temporal changes. The test dataset has a size of around 12K videos. We use their variants Mini Kinetic-C and Mini SSV2-C (Yi et al., 2021) to evaluate the robustness of models against corruptions. These two datasets apply 12 types of corruptions arising in nature on the original clean test datasets. Each corruption has 5 levels of severities. The sample of Mini Kinetics-C is shown in supplementary.

Metrics. The classification accuracy on corrupted data is the most common metric to measure the corruption robustness of models. In our experiments, the corrupted datasets have 12 types of corruptions and each has 5 levels of severities. We use mPC (stands for mean performance on corruptions) to evaluate the overall robustness. We compute mPC by averaging the classification accuracy as:

$$mPC = \sum_{c=1}^{12} \sum_{s=1}^{5} CA_{c,s}, \tag{4}$$

where $CA_{c,s}$ is the classification accuracy on corruption c at level s.

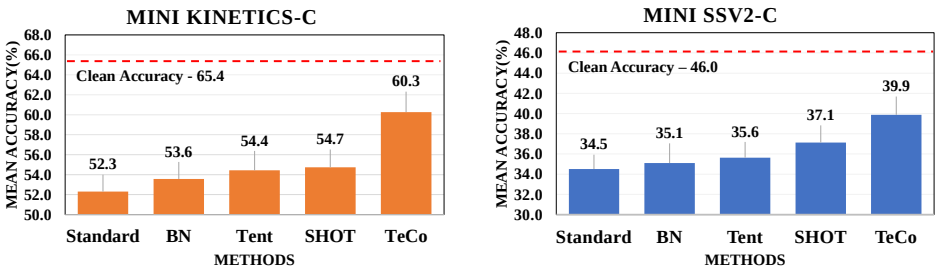

Figure 2: Mean Robustness on Mini Kinetics-C and Mini SSV2-C of methods. TeCo reduces the gap between model accuracy on clean and corrupted data significantly.

Models. The test-time optimization techniques can usually be applied across architectures. We use several classic 2D and 3D CNN-based architectures as the backbone to show the superiority of our method TeCo. For 2D CNN, we choose vanilla ResNet18 and its variant TAM-ResNet18 (Fan et al., 2019) as the model architecture. The vanilla ResNet18 treats single image frames in the video as the input data. It has only an average fusion at the output stage for the overall video classification. TAM-ResNet18 integrates a temporal module in the ResNet architecture. It helps the model store more temporal information for classification. Hence, it obtains improvements in clean accuracy, especially on the SSV2 dataset. For 3D CNN, we use the 3D version ResNet18 (Hara et al., 2017) for training and evaluation. The 3D convolution layers enable it to capture sufficient spatio-temporal features in an end-to-end training manner.

Baseline. Though the video classification area lacks research in test-time optimization, we import the baseline methods in image-based test-time optimization. BN (test-time batch normalization) is a simple method that adapts the batch normalization statistics with test-time data. Tent extends from BN by updating the transformation parameters in the normalization layers, with an objective of entropy minimization. SHOT(Liang et al., 2020) is well-known for combining entropy minimization and pseudo-labeling. All the methods can improve the corruption robustness of image-based deep learning models. We fit them into video classification frameworks.

Trainig and Evaluation Setup. We separate the setup of the experiment into three stages: pre-training, test-time optimization, and test-time evaluation. In the pretraining stage, we use uniform sampling to create 16-frame-length input data. Then we use multi-scale cropping on the input for data augmentation and resize the cropped frames to a size of 224. We train the models with an initial learning rate of 0.01 and a cosine annealing learning rate schedule. In test-time optimization, we use the pre-trained model for network weight initialization and update the model parameters for one epoch. For standard (without test-time optimization), BN, Tent, and SHOT methods, we use uniform sampling to extract input from corrupted test data. We apply both uniform and dense sampling to create input for TeCo. In all the test-time optimization experiments, we follow the offline adaptation setting in Wang et al. (2021a). For the optimization, we use SGD with momentum. On Mini Kinetics-C, we use a batch size of 32 and a learning rate of 0.001; while for Mini SSV2-C, we use the same batch size but a learning rate of 0.00001. After adapting the models with test data, we freeze the model weights and evaluate on the corrupted data. The inference is only based on the global pathway.

4.1 Experimental Results

mPC across architectures and datasets. Benefiting from the temporal coherence, our method TeCo consistently outperforms image-based test-time optimization methods across architectures and datasets. Table 1 shows the mPC on Mini Kinetics-C of various methods. Compared with the standard inference, BN improves the mPC by only 1∼2% because it only adapts BN statistics; Tent and SHOT increase the robustness by a larger margin, due to their updates on more parameters. However, the improvements are not consistent across architectures. For TAM, the Tent degrades the performance. We hypothesize that Tent fully removes the training time BN statistics, but the test-time data is not sufficient to make the parameters reach the global optimum. Meanwhile, our proposed TeCo achieves the best performance, enhancing the mPC by 7.2∼9.2% on various architectures. In Figure 2, we show the mPC on various architectures, including 3D ResNet18, ResNet18

Table 1: mPC across architectures on Mini Kinetics-C and Mini SSV2-C. TeCo outperforms other baseline methods on different architectures and datasets. **Clean Acc** is the accuracy of model tested on clean data.

	Backbone	Clean Acc	Standard	BN	Tent	SHOT	TeCo
Mini Kinetics-C	3D ResNet18	61.7	49.4	50.6	53.9	52.6	**56.9**
	ResNet18	66.0	51.6	53.0	55.6	53.2	**60.8**
	TAM-ResNet18	68.5	55.9	57.1	53.8	58.4	**63.4**
Mini SSV2-C	3D ResNet18	52.2	39.3	40.0	39.9	42.4	**45.7**
	ResNet18	30.2	20.0	20.3	22.5	23.8	**24.5**
	TAM-ResNet18	55.5	44.2	45.0	44.5	45.2	**49.4**

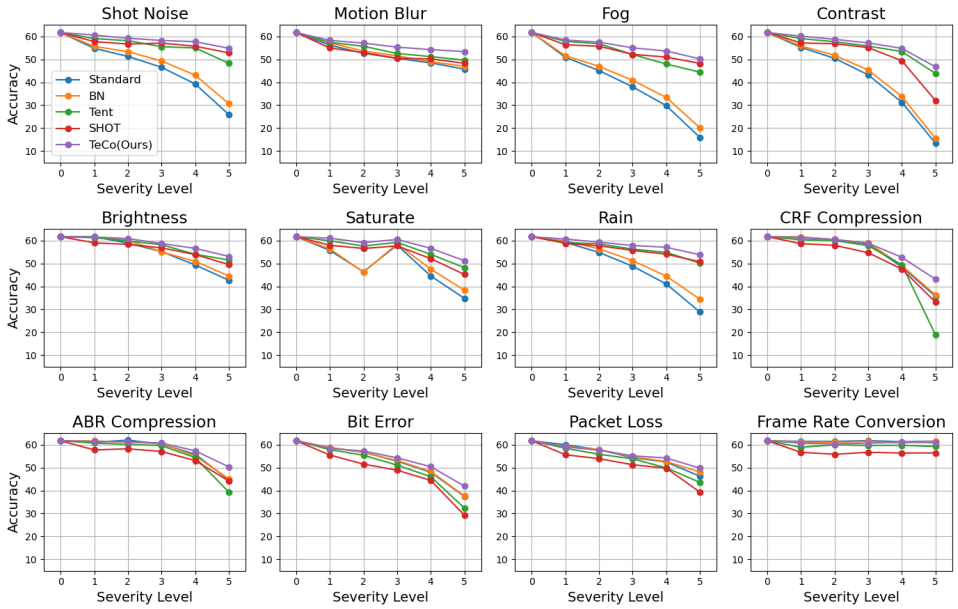

Figure 3: Full results on Mini Kinetics-C, with a backbone of 3D ResNet18. The accuracy of standard and BN methods drops sharply when the models encounter severe corruptions like noise, fog, rain, and contrast change. TeCo remains robust against corruptions at even level-5 severity.

and TAM. There is a small gap of 5.1% between the accuracy testing on clean data and the mPC results achieved by TeCo.

On Mini SSV2-C, our method TeCo surpasses other baseline methods significantly. Table 1 demonstrates the overall mPC of methods on Mini SSV2-C. We find the ResNet18-based method has an obvious degradation in the robustness. Because this method has no module in capturing temporal information except output fusion, their performance on Mini SSV2 is relatively poor when the Mini SSV2 replies more on temporal information for classification. Similar to the phenomenon on Mini-Kinetics-C, BN increases the mPC by around 1%; Tent and SHOT show a diverging enhancement across architectures, from 0.3∼3.8%. TeCo consistently improves the corruption robustness on various architectures from 4.5∼6.4%. Horizontally comparing the performance on Mini Kinetics-C and Mini SSV2-C, there is a larger gap between clean accuracy and mPC on Mini SSV2-C from absolute and relative aspects, as shown in Figure 2. We hypothesize that the corrupted temporal information is hard to be compensated, but the spatial semantics can be extracted from the neighboring frames with the nature of temporal coherence.

Accuracy w.r.t corruption and severity. When digging deeper into the robustness of methods, we find that TeCo achieves superior performance on corruptions at different levels of severities. Figure 3 shows the complete results on various corruptions from Mini Kinetics-C, with a backbone of 3D ResNet18. The horizontal axis indicates the severity of corruption. When the value is 0, it

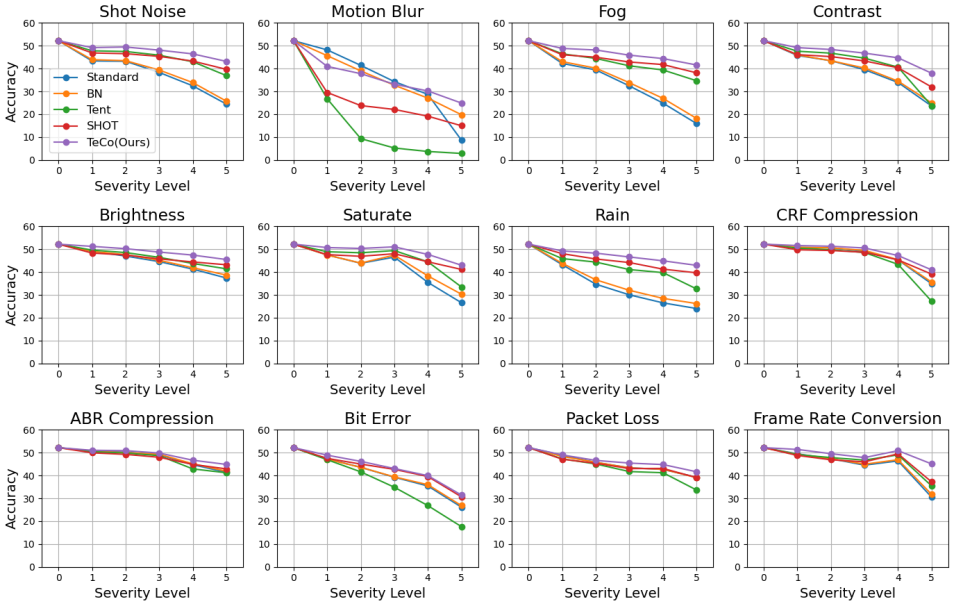

Figure 4: Full results on Mini SSV2-C, with a backbone of 3D ResNet18. Tent becomes vulnerable to motion blur and bit error, while TeCo lies above other methods on most types of corruptions.

corresponds to the accuracy on clean test data. We find the standard and BN methods have much worse performance compared to Tent, SHOT, and TeCo, when data is corrupted by shot noise, fog, contrast, saturate change, and rain. We hypothesize that simply adapting the batch normalization statistics is not able to correct the shifts raised by these corruptions. Tent, SHOT and TeCo demonstrate a similar trend when they encounter corruptions at various severity levels. However, TeCo always lies at the top of the trend lines, especially at a severity level of 5. For instance, TeCo maintains the accuracy of 46.7% at level-5 contrast changes, while the accuracy of standard and BN methods drops to 12%. It shows that TeCo benefits from the temporal coherence in video data, apart from an end-to-end test-time optimization scheme.

Figure 4 shows the complete results on Mini SSV2-C. Apart from the corruptions which cause severe accuracy degradation in Mini Kinetics-C, the corruptions like motion blur, bit error, and frame rate conversion also lead to significant drops in accuracy in Mini SSV2-C. Intuitively, these three types of corruption have more impact on temporal information. For example, bit error propagates the perturbation in the consecutive frames, and frame rate conversion changes the speed of motions in the video clips. The performance of Tent is devastating when facing motion blur and bit error. In contrast, TeCo, which uses a balanced test-time optimization framework, guarantees performance even though the test-time data has a large shift from the clean data. As a result, TeCo achieves consistent robustness improvements on different corruptions across datasets.

4.2 Ablation Studies

Disentangle Modules in TeCo. Table 2 shows the utility of three key components in TeCo: test-time optimization strategy, global and local pathways integration, and attentive temporal coherence regularization with local content. The test-time optimization strategy balances training and test-time parameters and statistics, which is more effective than other baseline methods in improving video classification corruption robustness. Global and local pathways provide complementary information for optimization. If we only use uniform sampling for entropy minimization and temporal coherence regularization, the improvement is as low as 0.1% on Mini SSV2-C. When we apply the regularization on local content, the mPC increases by 1% and 1.3% respectively.

Regularize Middle Layer Feature. Table 3 shows the comparison results of the attentive temporal coherence regularization module added after different blocks of 3D ResNet18. The performances after res_{1-3} are similar, while there is a slight drop after res_4. We hypothesize the deeper layer will

Table 2: Ablating components of TeCo on Mini Kinetics-C and Mini SSV2-C. The test-time optimization strategy, local pathway (l-path), and attentive temporal coherence regularization improve robustness.

model, 3D R18	Standard	SHOT	TeCo (w/o l-path)	TeCo (uniform)	TeCo
Mini Kinetics-C	49.4	52.6	55.9	56.5	**56.9**
Mini SSV2-C	39.3	42.4	44.4	44.5	**45.7**

Table 3: Temporal coherence regularization module is added into different blocks. All entries with 3D ResNet18 and the results are on Mini Kinetics-C.

model, 3D R18	mPC
baseline	49.4
res_1	56.6
res_2	**56.9**
res_3	56.6
res_4	56.2

Table 4: TeCo uses different batch size. All entries with 3D ResNet18 and the results are on Mini Kinetics-C.

Batch Size	mPC
8	56.6
16	56.7
32	**56.9**
64	56.6

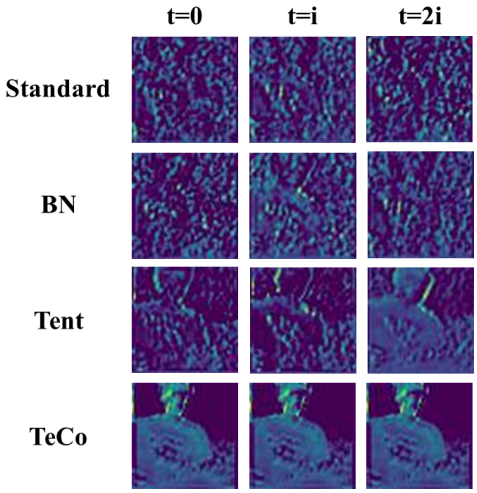

Figure 5: We visualize res_1 feature maps of consecutive frames. The time gap between frames is $i = 1$. TeCo generates smoother feature maps in both spatial and temporal dimensions.

generate more distinguishable features. It benefits from variety instead of consistency for classification.

Adjust Batch Size. Table 4 studies the impact of batch size on performance of TeCo. The mPC keeps improving when we increase the batch size from 8 to 32, while it drops when we use the batch size of 64. Because we optimize the model for one epoch for a fair comparison, a larger batch size will lead to fewer iterations of updates. The batch size of 32 balances the amount of data in one batch and the number of iterations in one epoch, which enables models to obtain the best performance.

Visualize Space-Time Feature Map. Figure 5 shows the feature maps of noise corrupted video after res_1 stages. Horizontally, we visualize the features of different frames. The time gap between neighboring frames is $i = 1$. Standard and BN methods fail to recover human-recognizable semantics from the noise-corrupted frames. Tent obtains noisy outlines along the temporal dimension. TeCo removes the noise and generates temporal coherent feature maps, indicating that TeCo helps the model obtain smoother and more consistent features.

5 Conclusion

TeCo is a test-time optimization technique for improving the corruption robustness of video classification models, which updates model parameters during testing by two objectives with self-supervised learning: TeCo uses global information for entropy minimization, and it also applies attentive temporal coherence regularization on local information. Benefiting from long-term and short-term spatio-temporal information, TeCo achieves significant corruption robustness improvement on Mini Kinetics-C and Mini SSV2-C. We hope TeCo becomes a new baseline method that makes video classification models more reliable and robust in real-world deployment.

REFERENCES

Fatemeh Azimi, Sebastian Palacio, Federico Raue, Jörn Hees, Luca Bertinetto, and Andreas Dengel. Self-supervised test-time adaptation on video data. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 3439–3448, 2022.

Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? In *ICML*, volume 2, pp. 4, 2021.

Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6299–6308, 2017.

Chun-Fu Chen, Rameswar Panda, Kandan Ramakrishnan, Rogerio Feris, John Cohn, Aude Oliva, and Quanfu Fan. Deep analysis of cnn-based spatio-temporal representations for action recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021.

Debidatta Dwibedi, Yusuf Aytar, Jonathan Tompson, Pierre Sermanet, and Andrew Zisserman. Temporal cycle-consistency learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

Quanfu Fan, Chun-Fu Richard Chen, Hilde Kuehne, Marco Pistoia, and David Cox. More is less: Learning efficient video representations by big-little network and depthwise temporal aggregation. *Advances in Neural Information Processing Systems*, 32, 2019.

Christoph Feichtenhofer. X3d: Expanding architectures for efficient video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 203–213, 2020.

Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 6202–6211, 2019.

Robert Geirhos, David HJ Janssen, Heiko H Schütt, Jonas Rauber, Matthias Bethge, and Felix A Wichmann. Comparing deep neural networks against humans: object recognition when the signal gets weaker. *arXiv preprint arXiv:1706.06969*, 2017.

Robert Geirhos, Carlos R Medina Temme, Jonas Rauber, Heiko H Schütt, Matthias Bethge, and Felix A Wichmann. Generalisation in humans and deep neural networks. In *Proceedings of the Neural Information Processing Systems (NIPS)*, 2018.

Ross Goroshin, Joan Bruna, Jonathan Tompson, David Eigen, and Yann LeCun. Unsupervised learning of spatiotemporally coherent metrics. In *Proceedings of the IEEE international conference on computer vision*, pp. 4086–4093, 2015.

Raghav Goyal, Samira Ebrahimi Kahou, Vincent Michalski, Joanna Materzynska, Susanne Westphal, Heuna Kim, Valentin Haenel, Ingo Fruend, Peter Yianilos, Moritz Mueller-Freitag, et al. The" something something" video database for learning and evaluating visual common sense. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 5842–5850, 2017.

Kensho Hara, Hirokatsu Kataoka, and Yutaka Satoh. Learning spatio-temporal features with 3d residual networks for action recognition. In *Proceedings of the IEEE international conference on computer vision workshops*, pp. 3154–3160, 2017.

Dan Hendrycks and Thomas Dietterich. Benchmarking neural network robustness to common corruptions and perturbations. In *International Conference on Learning Representations*, 2019.

Dan Hendrycks, Norman Mu, Ekin Dogus Cubuk, Barret Zoph, Justin Gilmer, and Balaji Lakshminarayanan. Augmix: A simple data processing method to improve robustness and uncertainty. In *International Conference on Learning Representations*, 2020.

Yujia Huang, James Gornet, Sihui Dai, Zhiding Yu, Tan Nguyen, Doris Tsao, and Anima Anandkumar. Neural networks with recurrent generative feedback. *Advances in Neural Information Processing Systems*, 33:535–545, 2020.

Dinesh Jayaraman and Kristen Grauman. Learning image representations tied to ego-motion. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1413–1421, 2015.

Christoph Kamann and Carsten Rother. Benchmarking the robustness of semantic segmentation models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8828–8838, 2020.

Oğuzhan Fatih Kar, Teresa Yeo, Andrei Atanov, and Amir Zamir. 3d common corruptions and data augmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18963–18974, 2022.

Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large-scale video classification with convolutional neural networks. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pp. 1725–1732, 2014.

Dan Kondratyuk, Liangzhe Yuan, Yandong Li, Li Zhang, Mingxing Tan, Matthew Brown, and Boqing Gong. Movinets: Mobile video networks for efficient video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 16020–16030, 2021.

Nuo Li and James J DiCarlo. Unsupervised natural experience rapidly alters invariant object representation in visual cortex. *science*, 321(5895):1502–1507, 2008.

Yanghao Li, Chao-Yuan Wu, Haoqi Fan, Karttikeya Mangalam, Bo Xiong, Jitendra Malik, and Christoph Feichtenhofer. Mvitv2: Improved multiscale vision transformers for classification and detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4804–4814, 2022.

Jian Liang, Dapeng Hu, and Jiashi Feng. Do we really need to access the source data? Source hypothesis transfer for unsupervised domain adaptation. In *Proceedings of the 37th International Conference on Machine Learning*, pp. 6028–6039, 2020.

Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 7083–7093, 2019.

Yuejiang Liu, Parth Kothari, Bastien van Delft, Baptiste Bellot-Gurlet, Taylor Mordan, and Alexandre Alahi. Ttt++: When does self-supervised test-time training fail or thrive? In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, volume 34, pp. 21808–21820. Curran Associates, Inc., 2021. URL https://proceedings.neurips.cc/paper/2021/file/b618c3210e934362ac261db280128c22-Paper.pdf.

Claudio Michaelis, Benjamin Mitzkus, Robert Geirhos, Evgenia Rusak, Oliver Bringmann, Alexander S Ecker, Matthias Bethge, and Wieland Brendel. Benchmarking robustness in object detection: Autonomous driving when winter is coming. *arXiv preprint arXiv:1907.07484*, 2019.

Shuaicheng Niu, Jiaxiang Wu, Yifan Zhang, Yaofo Chen, Shijian Zheng, Peilin Zhao, and Mingkui Tan. Efficient test-time model adaptation without forgetting. *arXiv preprint arXiv:2204.02610*, 2022.

Evgenia Rusak, Lukas Schott, Roland Zimmermann, Julian Bitterwolf, Oliver Bringmann, Matthias Bethge, and Wieland Brendel. Increasing the robustness of dnns against image corruptions by playing the game of noise. *arXiv preprint arXiv:2001.06057*, 2020.

Steffen Schneider, Evgenia Rusak, Luisa Eck, Oliver Bringmann, Wieland Brendel, and Matthias Bethge. Improving robustness against common corruptions by covariate shift adaptation. *Advances in Neural Information Processing Systems*, 33:11539–11551, 2020.

Assaf Shocher, Nadav Cohen, and Michal Irani. "zero-shot" super-resolution using deep internal learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3118–3126, 2018.

Manli Shu, Weili Nie, De-An Huang, Zhiding Yu, Tom Goldstein, Anima Anandkumar, and Chaowei Xiao. Test-time prompt tuning for zero-shot generalization in vision-language models. *arXiv preprint arXiv:2209.07511*, 2022.

Karen Simonyan and Andrew Zisserman. Two-stream convolutional networks for action recognition in videos. *Advances in neural information processing systems*, 27, 2014.

Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei Efros, and Moritz Hardt. Test-time training with self-supervision for generalization under distribution shifts. In *International conference on machine learning*, pp. 9229–9248. PMLR, 2020.

Dimitris Tsipras, Shibani Santurkar, Logan Engstrom, Alexander Turner, and Aleksander Madry. Robustness may be at odds with accuracy. *arXiv preprint arXiv:1805.12152*, 2018.

Dequan Wang, Evan Shelhamer, Shaoteng Liu, Bruno Olshausen, and Trevor Darrell. Tent: Fully test-time adaptation by entropy minimization. In *International Conference on Learning Representations*, 2021a.

Haotao Wang, Chaowei Xiao, Jean Kossaifi, Zhiding Yu, Anima Anandkumar, and Zhangyang Wang. Augmax: Adversarial composition of random augmentations for robust training. *Advances in neural information processing systems*, 34:237–250, 2021b.

Limin Wang, Yuanjun Xiong, Zhe Wang, Yu Qiao, Dahua Lin, Xiaoou Tang, and Luc Van Gool. Temporal segment networks: Towards good practices for deep action recognition. In *European conference on computer vision*, pp. 20–36. Springer, 2016.

Limin Wang, Zhan Tong, Bin Ji, and Gangshan Wu. Tdn: Temporal difference networks for efficient action recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1895–1904, 2021c.

Qin Wang, Olga Fink, Luc Van Gool, and Dengxin Dai. Continual test-time domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7201–7211, 2022.

Xiaolong Wang, Ross Girshick, Abhinav Gupta, and Kaiming He. Non-local neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7794–7803, 2018.

Xiaolong Wang, Allan Jabri, and Alexei A Efros. Learning correspondence from the cycle-consistency of time. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 2566–2576, 2019.

Laurenz Wiskott and Terrence J Sejnowski. Slow feature analysis: Unsupervised learning of invariances. *Neural computation*, 14(4):715–770, 2002.

Justin N Wood. A smoothness constraint on the development of object recognition. *Cognition*, 153: 140–145, 2016.

Justin N Wood and Samantha MW Wood. The development of newborn object recognition in fast and slow visual worlds. *Proceedings of the Royal Society B: Biological Sciences*, 283(1829): 20160166, 2016.

Min Wu and Marta Kwiatkowska. Robustness guarantees for deep neural networks on videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

Cihang Xie, Yuxin Wu, Laurens van der Maaten, Alan L Yuille, and Kaiming He. Feature denoising for improving adversarial robustness. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 501–509, 2019.

Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 305–321, 2018.

Chenyu Yi, Siyuan Yang, Haoliang Li, Yap-peng Tan, and Alex Kot. Benchmarking the robustness of spatial-temporal models against corruptions. In *Advance in Neural Information Processing Systems Track on Datasets and Benchmarks*, 2021.

Stephan Zheng, Yang Song, Thomas Leung, and Ian Goodfellow. Improving the robustness of deep neural networks via stability training. In *Proceedings of the ieee conference on computer vision and pattern recognition*, pp. 4480–4488, 2016.