Reliable Traffic Sign Recognition System

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Abstract*—Traffic sign detection and recognition is an important part of Advance Driving Assistance Systems (ADAS), which aims to provide assistance to the driver, autonomous driving, or even monitoring of traffic signs for maintenance. Particularly, misclassification of traffic signs may have severe negative impact on safety of drivers, infrastructures, and human in the surrounding environment. In addition to shape and colors, there are many challenges to recognize traffic signs correctly such as occlusion, motion blur, visual camera's failures, or physically altering the integrity of traffic signs. In Literature, different machine learning based classifiers and deep classifiers are utilized for Traffic Sign Recognition (TSR), with a few studies consider sequences of frames to commit final decision about traffic signs. This paper proposes a robust TSR against different attacks/failures such as camera related failures, occlusion, broken signs, and patches inserted on traffic signs. We are planning to utilize generative adversarial networks to corrupt images of traffic signs and investigate the robustness of TSR. Furthermore, we are currently working on designing a failure detector, which will help the TSR in advance before recognition, whether images are corrupted with some type of failure. Our conjecture is that failure detector with classifiers will improve the robustness of TSR system.

***Keywords*—Traffic Sign Recognition, Deep Learning, Camera Failures, Generative Adversarial Networks**

I. Introduction and Background

Traffic Sign Recognition (TSR) is an important component of Advance Driving Assistance Systems (ADAS), which aim to recognize traffic signs from images captured by cameras installed on vehicles. By nature, human drivers can miss or misinterpret a traffic sign due to distraction, tiredness, or any physical fatigue. As an alternative, automatic TSR systems i) pre-process images captured by input cameras, ii) extract relevant features and then, ii) feed those features into Machine Learners (MLs) that automatically perform recognition. Just like humans, automatic TSR systems can also misinterpret the detected traffic signs. Therefore, TSR systems are considered safety critical system, whose misclassifications may result in severe consequences to humans and environment. As such, researchers are putting more effort in building reliable TSR systems, which provide timely actionable information.

There are many reasons behind the misinterpretation of traffic sign by TSR such as camera failures [3], environmental conditions, occlusion, broken traffic signs, and insertion of patches or unintentional writing etc., on traffic signs. The main challenge is to devise such a TSR strategy which is more robust against such failures. In literature, different TSR strategies are applied using traditional machine learning or deep classifiers, which process single frame captured by camera. In our previous work [4], we performed comparison of deep classifiers and traditional machine learning classifiers such as KNN, or SVM, that are trained by feeding them handcrafted features, deep features, and their combinations. For the experimentation three benchmark dataset are utilized namely, i) Dataset of Italian Traffic Signs (DITS), ii) German Traffic Signs Recognition Benchmark (GTSRB), and iii) BelgiumTSC dataset . Available datasets report on sequences/sets of frames, we considered sliding windows approach for multi frame based TSR. Sliding windows based TSR i.e., deep classifier with meta-level classifier achieved perfect classification across all three datasets. Furthermore, we explored the robustness of deep classifiers for frames that are corrupted by camera failures such as broken lens, dead pixels, and no bayer filter. Different approaches for TSR are applied and found that few camera failures are more dangerous, which need further attention.

Generative Adversarial Networks (GANs) [1] are nowadays very popular to generate perturbed images starting from a clean set of images. GAN is used to obtain high-quality images generated through race between the generator and discriminator networks. Different GANs will be utilized for generation of faulty images. To overcome these failures, we are planning to design a failure detector (FD) which will notify in advance the TSR system about possible failure. For FD different approaches will be utilized in conjunction with TSR component. Furthermore, we are planning to consider many failures such as by inserting random patches on different position of the captured frames and through GANs produces corrupted images which may mislead the TSR. We are planning to include the corrupted images to the training process through data augmentation. By extending failure injected datasets through GANs, designing a FD and inserting corrupted images during training process, we aim to propose a strategy for building robust TSR systems and evaluate their robustness.

II. Motivation

In the last decades, researcher worked on automatic TSR systems to improve their performance. The majority of TSR systems process single image for the recognition, while there are few studies like [2] which consider sequences of images to improve the recognition of traffic signs. Under perfect environmental conditions, those approaches even guarantee perfect accuracy on public benchmark datasets.

However, in real scenarios there are many failures which can misguide the TSR system: camera failure, weather conditions and lens occlusions, to name a few. To the best of our knowledge, there is no comparative study which considers TSR performance with ongoing failures. As a result, we aim at generating synthetic datasets which will represent the real world failures that can happen to a TSR system. Furthermore, the mitigation or prevention of failures will be discussed in detail to benchmark different approaches on three available datasets.

III. Methodology

We first plan to generate different faulty datasets such as images corrupted due to different camera failures, insertion

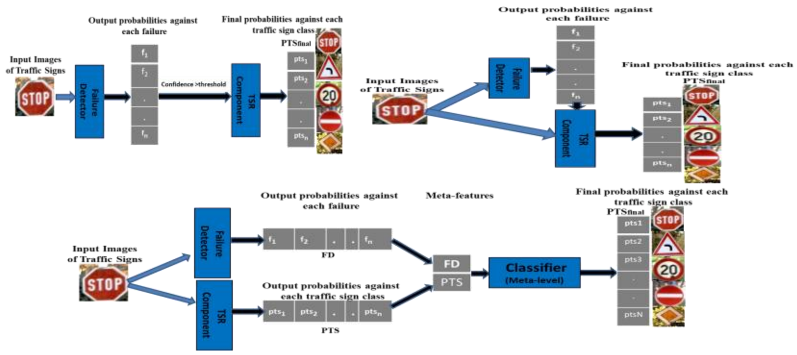

Figure 1: (a) up left, (b) up right and (c) bottom: Different strategies of applying a failure detector (FD) in conjunction with TSR component

of random patches, and images corrupted through GANs. This provides a rich set of images, which represent the real life effects of different failures that can happen to traffic signs. Those datasets will be used either for training or testing different ML-based TSR systems as follows:

- providing both clean and faulty images during training stage of models to mimic data augmentation, which should help in increasing classification accuracy of TSR even when dealing with faulty images in the test set.
- designing a Fault Detector (FD), or rather a binary classifier which aims at labeling images either as clean or corrupted. A more sophisticated FD could also be designed as a multi-class detector which labels images either as clean or according to their specific fault.

The first approach aims at building a more robust and reliable TSR system by working on the training phase of the ML algorithm which we chose as classifier. More specifically, providing faulty images during training will make the algorithm to learn also how to classify corrupted images, with beneficial effects on classification performance even without perfect environmental conditions.

We then explain the second approach above with the aid of Fig. 1. The figure shows three different ways in which a multi.-class FD could interact with the ML-based TSR to provide a unified, reliable, result. Noticeably, a binary FD is simpler to build than its multi-class counterpart: therefore, the discussion below may also apply to a binary FD. In Fig 1a, input images will first go through FD, which will provide the output probabilities for each class failure: those probabilities will then be analyzed and used to decide to either trust the input images as clean, or non-corrupted, or trigger alarms about a specific failure. Differently, the approach in Fig 1b provides images to both the FD and TSR system. Moreover, the output probabilities of FD are provided alongside the image to the TSR, enriching its feature set. Lastly, Fig 1c simplifies the approach above by running the FD and the TSR in parallel with the same input image. The output probabilities of both components are then provided as meta-features to a meta-level classifier that commits the final decision, mimicking a Stacking eta-learning ensemble.

We will exercise the four strategies above (i.e., one for enriching training set, and the three setups for detectors) independently to identify the most robust approach. To implement the FD, we will exercise both traditional supervised classifiers such as KNN, SVM, Gradient Boosting, Random Forest, and LDA, plus deep learning classifiers as AlexNet, Inceptionv3, MobileNetv2 with their own different parameters. Such implementation will take advantage of both MATLAB and Python libraries to perform experiments, and different classification performance metrics will be utilized to identify a more robust approach.

IV. Concluding remarks

This paper devises different strategies for building a reliable TSR system. We consider different failures that can happen to traffic sign in real life and create many faulty datasets starting from public benchmark datasets. We also discuss how to implement a Failure Detector and how it can effectively interact with a ML-based TSR system. Furthermore, we propose different ways to implement such detector, either as binary or multi-class. Overall, we conjecture that the proposed strategies and especially the combination of FD with TSR component will result in a reliable TSR system. To such extent, we are currently planning and running an experimental campaign that will experimentally verify or deny the conjecture above.

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References

[1] Creswell, Antonia, et al. "Generative adversarial networks: An overview." IEEE Signal Processing Magazine 35.1 (2018): 53-65.

[2] Yuan, Y., Xiong, Z., & Wang, Q. (2016). An incremental framework for video-based traffic sign detection, tracking, and recognition. IEEE Transactions on Intelligent Transportation Systems, 18(7), 1918-1929.

[3] Secci, F., & Ceccarelli, A. (2020, October). On failures of RGB cameras and their effects in autonomous driving applications. In 2020 IEEE 31st International Symposium on Software Reliability Engineering (ISSRE) (pp. 13-24). IEEE.

[4] Atif, M., Zoppi, T., Gharib, M., & Bondavalli, A. (2021, March). Quantitative comparison of supervised algorithms and feature sets for traffic sign recognition. In Proceedings of the 36th Annual ACM Symposium on Applied Computing (pp. 174-177).