Challenging Environments for Traffic Sign Detection: Reliability Assessment under Inclement Conditions

Dogancan Temel, Tariq Alshawi*, Min-Hung Chen*, and Ghassan AlRegib

Abstract—State-of-the-art algorithms successfully localize and recognize traffic signs over existing datasets, which are limited in terms of challenging condition type and severity. Therefore, it is not possible to estimate the performance of traffic sign detection algorithms under overlooked challenging conditions. Another shortcoming of existing datasets is the limited utilization of temporal information and the unavailability of consecutive frames and annotations. To overcome these shortcomings, we generated the CURE-TSD video dataset and hosted the first IEEE Video and Image Processing (VIP) Cup within the IEEE Signal Processing Society. In this paper, we provide a detailed description of the CURE-TSD dataset, analyze the characteristics of the top performing algorithms, and provide a performance benchmark. Moreover, we investigate the robustness of the benchmarked algorithms with respect to sign size, challenge type and severity. Benchmarked algorithms are based on state-of-the-art and custom convolutional neural networks that achieved a precision of 0.55 and a recall of 0.32, $F_{0.5}$ score of 0.48 and $F_2$ score of 0.35. Experimental results show that benchmarked algorithms are highly sensitive to tested challenging conditions, which result in an average performance drop of 0.17 in terms of precision and a performance drop of 0.28 in recall under severe conditions. The dataset is publicly available at https://ghassanalregib.com/cure-tsd/

Keywords—Traffic sign detection and recognition, traffic sign dataset, robustness evaluation under challenging conditions, machine learning for autonomous vehicles, convolutional neural networks

I. INTRODUCTION

The reliability of autonomous driving systems depends on the reliability of the core technologies that process and analyze sensed information. Therefore, algorithmic solutions behind the core technologies have to achieve a minimum performance under challenging conditions. Although extensive test driving have been a standard in the industry, there is an increase in demand for simulated approaches to evaluate the performance of advanced driver-assistance systems and autonomous functionalities. An essential component of simulations is the development of traffic datasets [1–12]. The focus of this paper is traffic sign detection that can only be sensed and processed through a vision system.

Møgelmose et al. [9] conducted a traffic sign detection survey, which included German traffic sign recognition benchmark [6, 7]. Swedish traffic signs dataset [5], RUG traffic sign image dataset [1], Stereopolis dataset [4], and Belgium traffic sign dataset [2]. Moreover in [9], the authors also introduced a traffic sign dataset denoted as LISA. In addition to aforementioned datasets, German traffic sign detection benchmark [8] and Belgium traffic sign classification [3] datasets were also used in the literature [13]. LISA dataset [9] images were captured in USA whereas other datasets [1–8, 10–12] originate from Europe. Even though majority of these datasets were focused on Europe, there are recent datasets that are based on Chinese traffic signs [10, 12]. Zhu et al. [10] introduced the Tsinghua Tencent 100K dataset, Yang et al. [11] introduced the Chinese Traffic Sign Dataset (CTSD), and Zhang et al. [12] extended the CTSD dataset with more images from Chinese highways to obtain the Changsha University of Science and Technology Chinese Traffic Sign Detection Benchmark (CCTSDB).

The majority of incumbent traffic datasets originate from video sequences. However, temporal relationships are overlooked because of discrete labels. Furthermore, these datasets are limited in terms of challenging environmental conditions and lack of performance analysis with respect to these conditions. Recent studies [14, 15] showed that adversarial examples can significantly degrade the traffic sign recognition and detection performance. Even though these recent studies shed a light on the vulnerability of existing methods, analyzed adversarial examples do not necessarily correspond to challenging conditions in the real world. We previously investigated the robustness of algorithms and APIs under simulated real-world challenging conditions [16, 17] but these studies were only limited to recognition tasks.

Previously, we organized a competition to assess the reliability of traffic sign detection algorithms as described the VIP Cup experience in a non-technical article, which included an overview of the competition setup and statistics, finalist teams

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Fig. 1: Challenging scene examples from the CURE-TSD dataset: darkening, exposure, snow, haze, and rain, respectively.
and their opinions [18]. In [16], we briefly investigated the robustness of recognition algorithms over cropped traffic signs and analyzed two other cropped sign datasets. On contrary to previous studies [16] [18], in this paper, we focus on the introduced detection dataset and benchmark algorithms in a comprehensive manner. The contributions of this paper are five folds.

- We provide a performance benchmark of the top performing algorithms along with algorithmic details for the first time since the competition.
- We analyze the robustness of benchmark algorithms with respect to challenge type and severity.
- We analyze the significance of sign size with respect to traffic sign detection performance.
- We include a detailed analysis of ten incumbent traffic sign datasets and a comparison with the introduced CURE-TSD dataset, which is the most comprehensive publicly-available traffic sign detection dataset with simulated challenging conditions, to the best of our knowledge.
- We describe the details of ground truth generation process, which is based on a publicly available annotation tool and a simulator engine. Moreover, we briefly describe the challenging condition synthesis framework.

II. RELATED WORK

Robust and reliable traffic sign detection is necessary to bring autonomous vehicles onto our roads. Therefore, researchers have been heavily focused on designing traffic sign detection and recognition algorithms. Initially, fully handcrafted methods dominated the traffic sign literature [11] [4] [5] [19]. The main mechanisms in these methods can be divided into two main blocks. First block is based on extracting descriptive information, which can be in the form of a feature, a descriptor, or any other representation. Second block is based on assessing the similarity/dissimilarity between extracted representations and predefined representations such as templates to determine the class of a traffic sign. Even though these handcrafted methods can lead to high detection or recognition performance in small scale datasets such as RUG [1], state-of-the-art methods were dominated by a wide range of machine learning methods in more recent datasets [2] [3] [9] [20] [26]. The machine learning techniques that lead to state-of-the-art performances in these studies include AdaBoost, neural networks, support vector machines, linear discriminant analysis, subspace analysis, ensemble classifiers, slow feature analysis, kd-trees, and random forests. Aforementioned studies mainly utilize machine learning techniques to learn the correspondence between handcrafted features/descriptors and traffic sign classes. However, Convolutional neural networks (CNNs) enabled learning visual representations in conjunction with their correspondences to sign classes directly from data, which led to state-of-the-art recognition and detection performances in recent studies [10] [12] [27] [35]. Even though CNNs are commonly used to eliminate designing features, they can also be combined with handcrafted features as shown in [11] [36].

There are numerous publicly-available datasets in the literature to validate traffic sign detection and recognition algorithms. The characteristics of these datasets are summarized in Table I which includes release year, number of video sequences, number of frames per video, number of total frames/images, number of total annotated frames/images, number of annotated signs, annotation information, resolution, number of sign types, annotated sign size, origin of the videos, acquisition device, training/test data splitting information, and challenging conditions. We have reported the characteristics of publicly available datasets based on either the information within the reference papers or our own analysis of dataset files. In the dataset table, there is a not-applicable expression (N/A) when a category does not apply to a dataset. Additional information about datasets are given in Section II-A main characteristics of these datasets are summarized in Section II-B and shortcomings are described in Section II-C.

A. Existing Datasets

RUG [1]: Grigorescu et al. [1] utilized distance sets for shape recognition, which also includes traffic signs. As test set, they introduced the RUS dataset that has 48 images of three traffic sign types captured in Netherland with color cameras. Images have a resolution of $360 \times 270$ and stored as PNG files.

BelgiumTS [2] and BelgiumTSC [3]: Timofte et al. [2] generated the BelgiumTS dataset, which was created with a van that had 8 roof-mounted cameras capturing images every meter. BelgiumTS includes a training set, a 2D testing set, and a 3D testing set. A subset of BelgiumTS images were selected to create Belgium traffic sign classification (BelgiumTSC) dataset in [3].

Stereopolis [4]: Belaroussi et al. [4] introduced the Stereopolis dataset, which contains images of complex urban scenes that were captured with a van every five minutes.

STS [5]: Larsson and Felsberg [5] generated the STS dataset. In the acquisition process, recording was started by a human operator whenever a traffic sign was visible and stopped when it was out of sight. In the annotations, visibility status includes visible, blurred, and occluded and road status includes current road or side road.

GTSRB [6, 7] and GTSDB [8]: Stallkamp et al. [6, 7] introduced the German traffic sign recognition benchmark (GTSRB) dataset. The sequence of images originating from one traffic sign instance was registered as track, which included 30 images by design. The training set maintained the temporal order of the images whereas the images in the test set were shuffled. The test set used for online competition [6] was later utilized as the validation set in [7]. German traffic sign detection benchmark (GTSDB) [8] is a successor to the GTSRB. In training/test data splitting, images of same real world traffic sign was assigned to either training or test set.

LISA [9]: Mogelmose et al. [9] introduced the LISA dataset, which was acquired with various systems including an Audi vehicle with Intelligent Urban Assist technology, a bike, and a Canon S95. After acquisition, each source video was split...
into smaller videos (tracks) that include up to 30 equidistant frames and annotated frames are at least 5 frames apart.

Tencent 100K [10]: Zhu et al. [10] introduced the Tsinghua-Tencent 100K dataset by extracting data from Tencent Street Views, which were captured with 6 SLR cameras every 10 meters and stitched together. The top and the bottom 25% of panoramic images were cropped and remaining images were divided vertically into 4 sub-images. Polygon and ellipse shapes were utilized to obtain pixel maps for traffic signs.

CTSD [11] and CCTSDB [12]: Yang et al. [11] introduced the Chinese Traffic Sign Dataset (CTSD), which includes images captured on highway, urban, and rural roads. Zhang et al. [12] introduced the Changsha University of Science and Technology Chinese Traffic Sign Detection Benchmark (CCTSDB) by extending the CTSD dataset with 5, 200 images captured in Chinese highways. Moreover, they augmented the original images by adding noise, changing illumination, and scaling to increase the diversity in the training of their models.

**B. Main Characteristics of Existing Datasets**

The majority of datasets summarized in Table I include images or groups of images denoted as tracks. There are 17 tracks in the LISA dataset, which includes ordered frames and the maximum number of frames in these tracks is 30. In addition to the LISA dataset, BelgiumTS dataset also includes ordered frames that correspond to 4 video sequences. The number of frames in these sequences vary from 2,001 to 6,201. The number of frames/images in existing datasets is in between 48 and 144,760 and the number of annotated signs in these datasets vary from none to 1,719,900. The annotation information in these datasets can include sign type, bounding box, challenge type and level.

| Release year | BelgiumTS | BelgiumTS | Stereopoulos | STS | GTSDB | LISA | GTSDB | TT-100K | CTSD | CCTSDB | CURE-TSD |
|--------------|-----------|-----------|--------------|-----|-------|------|-------|---------|------|--------|----------|
| Number of video sequences | N/A | N/A | N/A | N/A | 17 | N/A | N/A | N/A | N/A | 5,733 |
| Number of frames per video | 2,001 to 6,201 | N/A | N/A | N/A | N/A | up to 30 per track | N/A | N/A | N/A | 300 |
| Number of frames/images | 15,204 | 7,125 | 847 | 20,000 | 144,769 | 6,610 | 900 | 100,000 | 1,100 | 10,000 |
| Number of annotated frames/images | 51,840 | 7,855 | 1,206 | 30,000 | 1,574 | 1,206 | 30,000 | 1,574 | 13,361 |
| Number of annotated signs | 62 | 62 | 10 | 7 | 43 | 47 | 43 | 45 | 48 | 14 |
| Annotation information | Sign type, bounding box, 3D location | Sign type, bounding box | Sign type, bounding box | Sign type, bounding box | Sign type, bounding box, occlusion and road status | Sign type, bounding box, occlusion and road status | Sign type, bounding box, pixel map | Sign type, bounding box, challenge type and level |
| Resolution | 1,628x1,236 | 22x21 to 674x527 | 1,920x1,080 | 1,280x960 | 15x15 to 250x250 | 640x480 to 1,024x512 | 1,360x800 | 2,048x2,048 | 1,024x768 | 1,270x800 |
| Number of sign types | 9x10 to 562x438 | 5x5 to 263x248 | 3x5 to 263x248 | 15x15 to 250x250 | 15x15 to 250x250 | 15x15 to 250x250 | 6x6 to 167x168 | 16x128 | 2x7 to 397x394 | 26x26 to 573x557 |
| Origin of the videos | Captured in Belgium | Captured in France | Captured in Sweden | Captured in Germany | Captured in California | Captured in Germany | Captured in China | Captured in China | BelgiumTS, Unreal Engine, Adobe After Effects |
| Acquisition device | Color cameras | Color cameras | Color cameras | Point-Grey Chameleon color camera | Prosilica GC 1380CH color camera | Color and grayscale cameras | Prosilica GC 1380CH color camera | Color cameras | Color cameras | BelgiumTS Prosilica GC 1380CH |
| Training-test data splitting | 65%-35% | 65%-35% | 100% test | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% | Random splitting, validation:25%, training:70%, test:25% |
| Challenging conditions (*annotated) | illumination, occlusion, overcast | illumination, occlusion, deformation, perspective, size | illumination, occlusion, overcast | illumination, occlusion, size, blur perspective | illumination, occlusion*, shadow, blur* | overcast, rain | illumination, occlusion*, shadow, blur, reflection, color error, dirty lens, overcast | illumination, occlusion, overcast, shadow, rain, overcast | illumination, occlusion, shadow, rain, overcast | rain*, snow*, |
3D location, pixel map, visibility, occlusion, and road status. Bounding boxes were selected with the Video Annotator and Frame Annotator tool in the LISA dataset and the NISYS tool in the GTSRB and GTDB datasets. The resolution of full-scene images in the analyzed datasets vary from $360 \times 270$ to $2,048 \times 2,048$ and the annotated sign size vary from $2 \times 7$ to $573 \times 557$. We have analyzed the images along with the metadata in these datasets to obtain the dataset characteristics when they are not available in manuscripts. We have observed that some of the characteristics reported in corresponding papers including number of images, min/max resolution, and annotation size can slightly differ from the materials that are publicly available online.

Challenging conditions in traffic datasets are not explicitly described or analyzed in most of the corresponding publications. Therefore, we have visually inspected the images in these datasets to summarize existing conditions. Challenging conditions in detection datasets include illumination, occlusion, shadow, blur, reflection, codec error, dirty lens, overcast, and haze. In recognition datasets, we observe micro-level challenging conditions including perspective, size and deformation of the signs. The number of traffic sign types included in these datasets is in between 3 and 62. The majority of prior datasets were captured in Europe including Netherlands, Belgium, France, Sweeden, and Germany whereas LISA was captured in the USA and more recent datasets including TT-100K, CTSD, and CCTSDB were captured in China. Color cameras were utilized in the acquisition of majority of these datasets. However, grayscale cameras can be preferred to color cameras in mass production of cars to minimize overall cost. In the LISA dataset, some of the images were directly obtained from the sensors of an Audi A8 vehicle, which provided grayscale images. In some of the datasets, there is no split for training and testing whereas in other datasets, images were randomly split while satisfying predefined conditions.

## C. Shortcomings of Existing Datasets

The shortcomings of existing traffic sign datasets are five folds. First, the majority of existing datasets are limited in terms of challenging environmental conditions. Even though some of these datasets include numerous challenging conditions, these conditions are usually limited to marginal levels and they do not include severe conditions. Second, even some of the sequences in these datasets do have challenging conditions, corresponding metadata including condition type and level are not provided. Third, it is not possible to perform controlled experiments based on solely acquired traffic data because there is limited control over the conditions. Fourth, the majority of publicly-available datasets do not include videos and the ones that include videos do not provide labels for all the frames. Fifth, the size of existing datasets may not be sufficient to train models that are based on deep architectures. To compensate the shortcomings of existing datasets in terms of limited challenging conditions and corresponding metadata, lack of control in the environment, and restricted temporal information, we introduce the CURE-TSD dataset.

## III. CURE-TSD Dataset

### A. Reference Environments

The majority of publicly available datasets do not provide video sequences as reported in Table I. However, BelgiumTS [2] and LISA [9] datasets include video sequences. We preferred the BelgiumTS dataset because of the unavailability of videos sequences in the LISA dataset when this study was conducted. There were 8 cameras used in the acquisition of the BelgiumTS dataset and we utilized the sequences indexed with 03, which corresponds to the perspective of a driver without any car part blocking the view. In the BelgiumTS dataset, there are four sequences, which include 3,001, 6, 201, 2,001, and 4,001 frames. We generated sequences by combining 300 frames, which resulted in 49 challenge-free real-world video sequences. Moreover, we generated synthesized video sequences with a professional game development tool Unreal Engine 4 (UE4).

We utilized UE4 to synthesize video sequences because of three main advantages. First, objects in UE4 have metadata including position, size, and bounding box, which eliminates the manual labeling process. Second, environmental conditions including weather, time, and lighting can be fully controlled in UE4. We can change specific environmental conditions and levels while fixing other parameters to perform controlled experiments. Third, UE4 is relatively user friendly and is supported by a large developer community. We started data generation process by creating a virtual city that included roads, street lamps, traffic signs, and background environment. We added global lighting sources to make virtual environment more realistic. We generated a car object and linked that object with two functions, one for obtaining the location and the other one for showing the object on the screen. We attached a camera object to the car object, designed a driving path, created a path follower, configured the car speed, and placed the vehicle on the designed path. To match the number of real-world sequences, we generated 49 simulated sequences, which leads to a total of 98 challenge-free videos denoted as challenge-free sequences.

### B. Challenging Conditions

To emulate weather and vision system challenges, we utilized the Adobe(c) After Effects, which has been commonly used to synthesize visual effects and motion graphics at the post-production stage in previous studies [27,29]. Control over environmental conditions and levels enable scaling up generated dataset size significantly to test algorithms for robustness. Challenge levels were adjusted for each challenge type separately through visual inspection rather than numerical progression. We divided the challenges to five levels: level 1 does not affect the visibility of traffic signs from human perspective, level 2 affects the visibility of small and distant traffic signs, level 3 makes the visibility of small and distant traffic signs difficult, level 4 makes the visibility of small and distant traffic signs challenging, and level 5 makes the visibility of small and distant traffic signs nearly impossible. We generated 12 challenge types all of which correspond to conditions that can occur in real world. In Fig. 2, we show
sample images from the CURE-TSD dataset that includes all the challenging conditions for level 1, 3, and 5.

Decolorization tests the effect of color acquisition error, which was implemented with a color correction filter. Lens Blur and Gaussian Blur test the effect of dynamic scene acquisition, which was implemented with a smoothing operator. Unlike Lens Blur, Gaussian Blur is distributed in all directions, which results in less structured blurred scene. Codec Error tests the effect of encoder/decoder error, which was implemented with a time displacement filter. Darkening tests the effect of underexposure, which was implemented with an exposure filter. Dirty Lens tests the effect of occlusion because of dirt over camera lens, which was implemented by overlaying dirty lens images. Exposure tests the effect of overexposure in acquisition, which was implemented with an exposure filter. Noise tests the effect of acquisition noise, which was implemented using a noise filter. Rain tests the effect of occlusion due to rain, which was implemented using a gradient operator along with chroma filtering to obtain a blueish rain hue and a rain drop model. Shadow tests the effect of non-uniform lighting due to shadow, which was implemented using a blind-shaped operator. Snow tests the effect of occlusion due to snow, which was implemented using a glow operator along with chroma filtering to obtain a white hue and a snow fall model. Haze tests the effect of occlusion due to haze, which was implemented using a radial gradient operator with partial opacity, a smoothing operator, an exposure operator, a brightness operator, and a contrast operator. Location of the operators were manually controlled to create a sense of depth.

C. Traffic Signs

Real-world sequences in the introduced dataset is based on the BelgiumTS dataset, which includes 62 traffic sign types as summarized in Table I. While deciding on the type of traffic signs that should be annotated and included in the CURE-TSD dataset, we focused on two main criteria. First, not every sign type can be reasonably located in synthesized sequences. For example, we cannot reasonably include a level-crossing sign because there is no standard railroad feature in the utilized Unreal Engine 4 tool. Second, there are limited number of common signs between the package utilized in the generation of synthesized sequences and real-world sequences. Based on the aforementioned selection criteria, we provide 14 types of traffic signs with annotations in all the sequences, which include speed limit, goods vehicles, no overtaking, no stopping, no parking, stop, bicycle, hump, no left, no right, priority to, no entry, yield, and parking, as shown in Fig. 3. Each video sequence was processed with 12 challenge types as described in Section III-B except for haze in simulated sequences. To show the effect of challenging conditions over traffic signs, we show close up images of stop signs in Fig. 4.

D. Data Splitting

To split the challenge-free sequences into training and test sets, we followed a commonly utilized splitting ratio 7 : 3,
Fig. 3: Traffic sign samples from real-world (1st row) and synthesized sequences (2nd row).

Fig. 5: Ratio of signs in test set compared to overall dataset.

which resulted in 68 training videos and 30 test videos. We split challenge videos based on the sequence they originate from so that 7 : 3 ratio is maintained for challenge sequences as well. We started splitting video sequences based on the signs that appear the least and repeated the same procedure for the next less frequent sign type until each video sequence was classified. We obtained targeted split ratio for overall set with deviations up to 17% in individual sign types as summarized in Fig.5.

E. Ground Truth Generation

The annotations for BelgiumTS sequences were provided only for specific frames. However, our goal is to provide video sequences along with annotations for all frames to enable temporal information utilization. One option was to label those frames that lack annotations but that could have also led to inconsistency in the labelling process because of the inevitable differences across setups. Therefore, we annotated all frames in all BelgiumTS sequences using the Video Annotation Tool from Irvine, California (VATIC) [40]. We have utilized the pure JavaScript version which can directly run on a browser without requiring any specific installation. A traffic sign was annotated if at least half it was visible. A sample annotated frame with coordinate systems is shown in Fig.6.

The annotations in synthesized sequences were obtained from the Unreal Engine 4 (UE4), whose framework is given in Fig.7 in which grey arrows indicate auxiliary information utilized for coordinate verification. Provided framework includes the operations that were performed to resolve four main issues

Fig. 6: A sample annotated frame with the coordinate system.

Fig. 4: Stop sign samples under challenging conditions from real-world (1st row) and synthesized (2nd row) sequences.
in the annotation generation process. First, the built-in function for obtaining the bounding box coordinates in UE4 outputs 3D world coordinates. We projected 3D world coordinates to 2D display coordinates. Second, UE4 did not directly differentiate whether signs were inside the screen or not. To overcome the in/out of screen issue, we compared traffic sign coordinates with screen resolution and configured bounding boxes to cover the visible part. Third, UE4 detected all bounding boxes in the virtual environment regardless of the relative distances. To eliminate the visibility issue, we set a distance threshold to filter out signs that were not perceivable. Fourth, UE4 detected signs regardless of their direction. To resolve the direction issue, we calculated the angle between the direction of the vehicle and the direction of the front side of the sign and excluded the traffic signs with less than 90 degrees.

![Diagram](image.png)

**Fig. 7:** Annotation generation framework for synthesized sequences.

IV. BENCHMARK ALGORITHMS

We introduced the CURE-TSD dataset in Video and Image Processing (VIP) Cup 2017 competition whose theme was *Traffic Sign Detection under Challenging Conditions*. We hosted the competition as part of the IEEE International Conference on Image Processing (ICIP) 2017, which was sponsored by IEEE Signal Processing Society (SPS) and supported by the SPS Multimedia and Signal Processing (MMSP) Technical Committee. VIP Cup 2017 started with more than 250 requests from 147 parties from all around the world and 19 of these teams with a total of 80 members were able to attend the competition by satisfying the participation requirements. In this paper, we analyze the algorithms of top four performing teams and refer to the algorithms with the name of the teams as Neurons, PolyUTS, IIP, and Markovians.

A. Algorithm Neurons

**Preprocessing:** A customized preprocessing is performed over video frames depending on the challenge type to enhance traffic sign features. For video sequences with decolorization, darkening, exposure, shadow, snow, and haze, contrast-limited adaptive histogram equalization (CLAHE) was used. First, frames are converted from RGB domain to HSV domain. Then, different configurations of CLAHE are performed over the saturation and value channels depending on the challenge type. For video sequences with rain conditions, a ResNet type of CNN [41] is used to eliminate the effect of rain as in [42], which includes consecutive blocks that include convolution, batch normalization, and ReLU along with skip connections.

**TABLE II:** Challenge classification network of Neurons.

| Layer type | Kernel size & parameters |
|------------|--------------------------|
| input      | 3x309x407                |
| convolution| 3x3                      |
| max pooling| 4x4                      |
| convolution| 3x3                      |
| max pooling| 2x2                      |
| convolution| 3x3                      |
| max pooling| 2x2                      |
| convolution| 3x3                      |
| max pooling| 2x2                      |
| vectorization| -                      |
| fully connected with ReLU| 500                    |
| fully connected with Softmax| 12                     |

**Challenge classification:** Neurons detected challenge types with a CNN-based architecture similar to VGG-16 [43]. There are four main blocks with 2 convolutional layers, ReLU and a max-pooling layer. After the fourth layer, feature maps are vectorized and mapped to challenge types with two fully connected layers. Details of the challenge classification architecture are given in Table II.

**TABLE III:** Traffic sign classification network of Neurons.

| Layer type | Kernel size & parameters |
|------------|--------------------------|
| input      | 3x332x32                 |
| convolution| 3x3                      |
| max pooling| 2x2                      |
| drop out   | 0.25                     |
| convolution| 3x3                      |
| max pooling| 2x2                      |
| drop out   | 0.25                     |
| vectorization| -                      |
| fully connected with ReLU| 1024                   |
| fully connected with Softmax| 14                     |

**Detection:** Traffic signs are localized with challenge-specific
U-Net architecture [44] and detected signs are classified with another CNN architecture. Input images are resized to quarter of the original image resolution to reduce the number of parameters in the network. Localization architecture is based on downsampling stage and upsampling stage. In the downsampling stage, there are consecutive blocks that include convolution, batch normalization, ReLU, and max-pooling. Number of feature maps are doubled after each block. In the upsampling stage, input of each block is concatenated with a cropped feature map from the corresponding downsampling block. At the end of upsampling stage, convolutional layers map the features to binary classes as background or traffic sign. Localized regions are classified with a shallow CNN to recognize traffic sign types as summarized in Table III. There are two main blocks in the classification architecture, which includes two consecutive convolutional layers, a ReLU layer, a max-pooling layer followed by a dropout layer. Feature vectors are mapped to traffic sign types with two fully connected layers.

B. Algorithm PolyUTS

**Detection:** Input images are resized to 640x480 before being fed to the detection architecture. PolyUTS utilized pre-trained GoogLeNet [45] as feature extractor and features at the end of Inception 5B layer are fed into regression layers to obtain coordinates with confidence scores. Proposed detection-by-regression approach was inspired by state-of-the-art YOLO architecture [46]. In the YOLO architecture, feature vectors are concatenated and then fed to fully connected layers. However, PolyUTS passes the feature vectors one by one to the fully connected layers without concatenation to maintain the spatial information. Pretrained network outputs feature maps of size 20x15x1024. Then, each 20x15 feature map is fed to the regression stage that is based on two fully connected layers. Duplicated regions are eliminated with non-maximum suppression and a CNN-based architecture is used to classify region of interests into 14 classes of road signs and 1 class of non-sign region. Details of the traffic sign classification architecture are given in Table IV.

**TABLE IV:** Traffic sign classification network of PolyUTS.

| Layer type | Kernel size & parameters |
|------------|--------------------------|
| input      | 3x48x48                  |
| convolution with ReLU and batch norm | 7x7x100 |
| max pooling | 3x3 with stride 2         |
| convolution with ReLU and batch norm | 4x4x150 |
| max pooling | 3x3 with stride 2         |
| convolution with ReLU and batch norm | 4x4x250 |
| max pooling | 3x3 with stride 2         |
| vectorization | -                    |
| fully connected with ReLU and batch norm | 300   |
| fully connected with Softmax | 15    |

C. Algorithm IIP

**Detection:** IIP utilized a Faster R-CNN architecture [47] to detect traffic signs in the CURE-TSD dataset. Faster R-CNN is based on a region proposal network (RPN) and an object detector. RPN receives an image without size constraints and outputs a set of rectangular regions with an objectness score. Region proposals correspond to attention mechanisms [48], which tells the model where to pay attention. Zeiler and Fergus (ZF) [49] model is used to minimize the overall computation required for region proposal and object detection. Specifically, there are 5 sharable convolutional layers whose outputs are used for region proposals as well as object detection. A small network is slid over the last shared convolutional layer and at each sliding window, multiple regions proposals are predicted with various scale and aspect ratios. Training of Faster R-CNN is based on four steps. First, RPN is initialized with an ImageNet pretrained model and then fine-tuned end-to-end. Second, object detection network Fast R-CNN is also initialized by the ImageNet pretrained model and trained with the region proposals generated by RPN. Third, Fast R-CNN network is used to initialize the RPN training by fixing the shared convolutional layers and fine-tuning the remaining layers. Fourth, shared convolutional layers are kept fixed while fine-tuning the remaining layers of Fast R-CNN. Non-maximum suppression is used to merge highly overlapped bounding boxes and proposed regions are filtered with a fixed threshold to determine final results.

**TABLE V:** Shared convolutional layers between region proposal network and object detector in Markovians.

| Layer type | Kernel size & parameters |
|------------|--------------------------|
| input      | 224x224x3                |
| convolution with ReLU | 96x7x7 with a stride of 2 |
| max pooling and contrast norm | 3x3 with stride 2         |
| convolution with ReLU | 256x5x5 with a stride of 2 |
| max pooling and contrast norm | 3x3 with stride 2         |
| convolution with ReLU | 384x3x3 with a stride of 1 |
| convolution with ReLU | 256x3x3 with a stride of 1 |
| max pooling | 3x3 with stride 2         |

D. Algorithm Markovians

**Challenge Classification:** Markovians classified videos based on challenge types with a Recurrent CNN [51]. First layer of recurrent CNN is a standard feed-forward convolutional layer followed by max pooling. The following four layers are based on recurrent convolutional layers (RCL) with a max pooling layer in the middle. Adjacent RCL layers are connected with feed-forward connections. Pooling layers have a size of 3x3 with a stride of 2. There is a global max pooling layer at the end of last RCL layer for every feature map, which results in the feature vector representing the input image. Finally, a softmax classifier is used to map feature vectors to challenge categories. Estimated challenge classes are used to determine sign tracking mechanism.

**Detection:** Input images are resized to 640x480 before being fed to the detection architecture. Similar to IIP, Markovians
TABLE VI: Traffic sign classification network of Markovians.

| Layer type                | Kernel size & parameters |
|---------------------------|--------------------------|
| input                     | 64x64x3                  |
| convolution with ReLU     | 32x3x3                   |
| max pooling               | 2x2                      |
| drop out                  | 0.25                     |
| convolution with ReLU     | 64x3x3                   |
| convolution with ReLU     | 64x3x3                   |
| max pooling               | 2x2                      |
| drop out                  | 0.25                     |
| vectorization             | -                        |
| fully connected with ReLU | 512                      |
| drop out                  | 0.5                      |
| fully connected with Sigmoid | 24                     |

localized traffic signs with Faster R-CNN along with non-maximum suppression to merge highly overlapped estimations. A custom CNN-based approach is utilized to classify traffic signs whose details are provided in Table VI.

Tracking: In case of dirty lens and shadow, Kalman filtering is used to track signs. Estimated sign locations are considered valid if the distance between current measurement and prediction is less than 50 pixels. In case of other challenging conditions, traffic signs are tracked with Lucas-Kanade algorithm [52], which is a commonly used differential method for optical flow computation that is based on the assumption that flow between consecutive frames in a local neighborhood is constant.

E. Overview of the Benchmark Algorithms

We summarize the main characteristics of top performing traffic sign detection algorithms in the VIP Cup 2017 in Table VII. All of these algorithms are based on state-of-the-art architectures including VGG-16 [43], GoogLeNet [45], UNet [44], ResNet [41], YOLO [46], Recurrent CNN [51], Fast R-CNN [50], and Faster R-CNN [47]. There are four main differences between finalist algorithms and existing algorithms. First, video sequences were classified based on their challenge types by teams Markovians and Neurons. Second, video sequences were preprocessed based on challenge types to eliminate the effect of challenges by team Neurons. Third, team Markovians utilized temporal information in their algorithm, which is overlooked by majority of state-of-the-art architectures in the literature. Fourth, tracking mechanism is selected based on the classified challenge category by team Markovians.

V. PERFORMANCE BENCHMARK FOR CURE-TSD DATASET

A. Validation Metrics

We validated competing algorithms based on the detection files of testing sequences. Specifically, we computed Precision, Recall, and combination of these metrics (F-scores) to rank the performance of competing teams. Precision is calculated as

\[
\text{Precision} = \frac{TP}{TP + FP},
\]

where \(TP\) is the total number of true positive detections across all testing sequences, and \(FP\) is the total number of false positive detections across all testing sequences. A true positive is determined when a traffic sign is localized and recognized correctly and the bounding box of the detection overlaps with the bounding box of ground truth by at least 50%. Any other detection is considered as a false positive. Similarly, Recall is calculated as

\[
\text{Recall} = \frac{TP}{P},
\]

where \(TP\) is the total number of true positive detections across all testing sequences, and \(P\) is the total number of traffic signs in corresponding ground truth files. Furthermore, we use F-scores to combine Precision and Recall, which is formulated as

\[
F_\beta = (1 + \beta^2) \frac{\text{Precision} \cdot \text{Recall}}{\beta^2 \text{Precision} + \text{Recall}},
\]

where \(\beta\) is a parameter used to adjust relative significance of Precision and Recall. In our validation, we set \(\beta\) to 2 and 0.5, which are commonly utilized in the literature.

B. Results

Overall performance of competing teams in each category is summarized in Table VII. Higher score corresponds to better performance. The algorithm submitted by team Neurons outperforms all other submissions across all metrics as given in Table VII. In terms of Precision, teams PolyUTS and Markovians follow team Neurons. In all other metrics, team PolyUTS is the second and team Markovians is the third. Team IIP is the fourth best performing algorithm in terms of all the performance metrics in the IEEE VIP Cup 2017. When all performance metrics are considered for ranking, team Neurons is first, team PolyUTS is second, team Markovians is third, and team IIP is fourth.

In addition to ranking submitted algorithms, we also analyzed the performance of top four methods with respect to challenge level, traffic sign size, and challenge type. The performance of algorithms versus challenge levels is shown in Fig. 8 in which y-axis corresponds to performance metric values and x-axis corresponds to challenge levels. In terms of Recall and F2 score, algorithmic performance decreases as challenge levels increases. In terms of Precision, team Neurons follows a piece-wise linear decrease, team PolyUTS and team Markovians follow a parabolic decrease, and team IIP follows a linear decrease after level 3. In terms of F0.5 score, all metrics follow a monotonically decreasing behavior after level 1. Team Neurons and team IIP follow a piece-wise linear behavior whereas team PolyUTS and team Markovians follow a parabolic behavior. Aforementioned results indicate that training procedure of team IIP leads to highest Precision for sequences close to level 3 and highest
Fig. 8: Performance versus challenge levels.

\( F_{0.5} \) for sequences close to level 1. In all other scenarios, performance of algorithms degrade as challenge level increases. Varying size of traffic signs can be considered as another challenge source, whose level increases as sign size decreases. We report the performance of algorithms versus traffic sign size in Fig. 9 in which y-axis corresponds to performance

**TABLE VII: Characteristics and performance of top performing algorithms.**

| Team   | Challenge classification | Custom preprocessing | Detection                  | Tracking                  | Detection Performance |
|--------|--------------------------|----------------------|----------------------------|--------------------------|-----------------------|
| IIP    | -                        | -                    | Faster R-CNN               | -                        | 0.409 0.249 0.363 0.270 |
| Markovians | 24,839                  | Recurrent CNN        | Faster R-CNN-based localization | Kalman filtering, Lucas-Kanade | 0.509 0.250 0.422 0.279 |
| Neurons| CNN (~VGG) Color space transformation histogram equalization (CLAHE) ResNet-based denoising | Custom CNN-based recognition | Custom CNN-based recognition | -                       | 0.550 0.320 0.481 0.349 |
| PolyUTS| 24,860                   | -                    | CNN-based GoogLeNet-based localization | Custom CNN-based recognition | -                       | 0.504 0.284 0.436 0.311 |
values and x-axis corresponds to the size limit. Performance of algorithms were calculated for traffic signs whose maximum dimension (width or height) were smaller than the indicated size limit in the x-axis. As x-axis value increases, size of the signs included in the evaluation also increases, which makes it easier to localize and recognize signs. Therefore, we can consider x-axis values as indicator of challenge level, which increases as x-values get closer to the origin. All four algorithms follow a monotonically decreasing behavior with respect to size-based challenge level. Team Neurons leads to highest performance for all size levels in terms of all categories. For all size categories other than size limit 30, team IIP leads to lowest performance among all four methods. Team PolyUTS leads team Markovians in all the categories other than Precision when size limit is greater than 90. When size limit is 60 or less, team Markovians outperforms team PolyUTS.

Previously, we have investigated the effect of challenge level on the algorithmic performance. To understand the effect of challenging conditions, we also need to analyze the effect of challenge types. We report the performance of algorithms versus challenge type in Fig. 10 in which the y-axis corresponds to performance values and the x-axis corresponds to the top four algorithms from participating teams. Performance values corresponding to different challenge categories are represented with different colors and shapes. Overall performance of each team is shown with a horizontal dotted line. Performance change with respect to challenge types is more significant in team IIP compared to other algorithms. Specifically, overall performance of team IIP significantly degrades because of codec error in Precision and because of rain in all other metrics, which leads to inferior overall performance compared to top three performing methods. Team Markovians has a high performance variation in Precision and \( F_{0.5} \) whereas...
their performance variation is low in Recall and $F_2$. When low performance variation in Recall and $F_2$ is combined with the lowest performance in haze category, team Markovians performs similar to team IIP and both teams underperform compared to team PolyUTS and teams Neurons. Even though team Neurons has high performance variation in each metric, their relatively superior performance in the majority of challenge types makes them the top performing algorithm.

Aforementioned experiments focus on the detection performance in the test set, which includes a combination of real-world and synthesized data. However, to understand the effect of challenging conditions in different environments, we need to split the test set into real and synthesized sets and compare their performances. To measure the correlation between detection performances in real-world data and synthesized data, we computed the average Spearman correlation for Precision and Recall per challenging conditions as provided in Fig. 11. On average, Spearman correlation is 0.915 for Recall and 0.781 for Precision when real and synthesized results were compared. A high correlation between real-world and synthesized environment performances indicate that testing robustness of algorithms under challenging conditions in a simulator environment can be used to predict the robustness of algorithms in similar real-world scenarios.

Fig. 10: Performance versus challenge types.

Fig. 11: Average Spearman correlation between detection performances in real-world and synthesized environments.
VI. CONCLUSION

We performed a comprehensive analysis of publicly available traffic sign datasets. Based on our analysis, we observed that existing datasets are limited in terms of challenging environmental conditions and they lack metadata of challenge conditions and levels. Moreover, existing datasets are also limited in terms of size and annotated frames that are continuous. Finally, it is not possible to determine the relationship between individual environmental conditions and algorithmic performance because multiple conditions change simultaneously. To overcome the shortcomings in the traffic sign literature, we introduced the CURE-TSD dataset and organized the IEEE VIP Cup 2017 to benchmark algorithms under challenging conditions. All top performing algorithms are based on deep architectures whose performance degrade significantly under challenging conditions. Therefore, conducted study articulates the urgent need for developing more robust algorithms that can adapt to the variations in environmental conditions. To understand the effect of challenging conditions in different environments, we compared the detection performance variation in real-world data and synthesized data. Experimental results showed that there is a high correlation between real-world and synthesized performance variations, which indicates that testing robustness with simulator data can be used to predict the real-world reliability under similar scenarios.

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