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# VisibilityNet: Camera visibility detection and image restoration for autonomous driving

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## ABSTRACT

*Cameras sensors are crucial for autonomous driving as they are the only sensing modality that provide measured color information of the surrounding scene. Cameras are directly exposed to external weather conditions where visibility is dramatically affected due to various reasons such as rain, ice, fog, soil, ..etc. Hence, it is crucial to detect and remove the visibility degradation caused by the harsh weather conditions. In this paper, we focus mainly on soiling degradation. We provide methods for classification of the soiled parts as well as methods for estimating the scene behind the soiled parts. A new dataset is created providing manually annotated soiled masks knows as WoodScape dataset to encourage research in that area.*

## I INTRODUCTION

Autonomous Driving (AD) is becoming more mature in the automotive technology. AD can be described as a pipeline of algorithms that starts with data collection and ends with decisions applied to the actuators of the vehicle such as steering, acceleration and braking. Figure 2 illustrates the AD pipeline where data collected from the installed sensors is passed through high level semantic perception such as object detection and lane detection modules. Sensor Fusion is a critical module where different modalities are fused together for improving environment perception. Given the environment map, trajectory planning takes place and finally commands are sent over the vehicle network to control actuators. One of the main reasons for the vast improvement in AD is the development of more robust algorithms for Environment Perception as well as vehicle control. In certain conditions such as heavy rain, snow fog and off-road driving, environment perception module does not provide an accurate map. This in turn affects the trajectory planning and may comprise fatal risk for the passengers on board due to incorrect decisions taken by the AD system.

One of the main challenges is that cameras visibility can be dramatically affected by soiling. Figure 1 shows an example of the scene blindness when there is soil on the camera sensor. The figure demonstrates the impact of directly using the camera sensors without taking care of the visibility degradation that may occur due to camera sensor blindness, from rain or soil. It is shown that road segmentation is significantly degraded which may cause problems in free-space computation and hence increasing the risk of collision. Conventional methods to solve such limitations usually use special hardware that is designed specifically for this problem. Figure 3 shows a dedicated system that cleans the sensor to improve detection. Such systems are based on water tanks which are extra cost for the system in addition to their need to be maintained. Additionally some systems have an air blower for getting rid of the remaining water after cleaning. In this paper, we propose software algorithms that provide the same functionality at a much lesser cost.

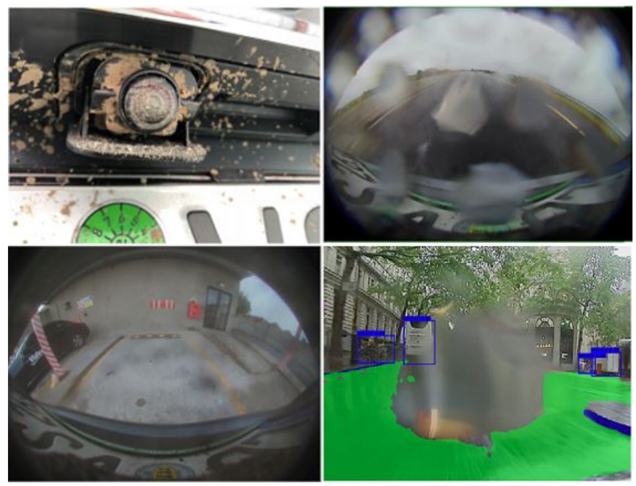

**Figure 1:** ***Top Left:*** *Soiled Camera.* ***Bottom Left:*** *Image produced from a soiled camera.* ***Top Right:*** *Image produced from camera in rainy weather.* ***Bottom Right:*** *Environment perception using soiled camera.*

Our contribution to this work includes:

- Empirical Evaluation of the impact on environment perception due to visibility impairment caused by environmental conditions.
- Discuss the challenges to solve the visibility problem by software solutions
- Introduce datasets to encourage research in this area.
- Propose CNN-based networks (software only solution) for image restoration after being blinded by weather conditions.

The rest of the paper is organized as follows: a review of the related work is presented in Section II. Our methodology including the dataset preparation and the used network architectures is detailed in Section III. Experimental setup and final results are illustrated in Section IV. Finally, Section V concludes the paper

## II RELATED WORK

Image restoration has been studied for autonomous driving application to improve the images quality affected due to low light and environmental conditions such as rain, haze, etc. and motion blurring which is resulted from high speed motion in the AD scenes. New computer vision methods have been introduced such as deraining [1], de-fogging [2] and de-hazing [3]. Image restoration becomes dependant on the blindness type, for instance, if water drop is settled over a camera lens, the scene at that region becomes semi-transparent. In that area, unlike mud blindness, there is still some information that is received from behind the drop of water, which will encourage the usage of specific computer vision algorithms that may not be beneficial with completely opaque blindness areas. The work of [4] provides a comprehensive analysis about rain drops removal for image restoration. In [5], the problem of rain removal using a two-stage recurrent network is investigated. In [6], a progressive recurrent de-raining network is addressed by repeatedly unfolding a ResNet with recurrent Layer. In [7], a new dataset of $\approx$ 29.5k image pairs for both rain and no-rain states is released and a model is proposed to remove rain streaks in a local-to-global manner. In [8], a method for improving segmentation from rainy images has been introduced, in addition to a dataset of rainy and clear image pairs which is used for restoration.

Recently, GANs[9] have demonstrated huge success in image generation, where unprecedented ability in synthesizing realistic-looking images is illustrated in [10]. On the other hand, GANs have difficulties in generation of some classes compared to others when trained on multi-class datasets such as ImageNet [11]. Self attention mechanism has been introduced in [12] to tackle this problem.

In [13], soiling detection for autonomous driving application has been thoroughly explained where the idea of how GANs could be utilized for data augmentation for soiling. A more formal introduction to the soiling detection and categorization is provided in [14], where the problem is formalized as a multi-label classification task.

In AD, the images are an input to computer vision algorithms which try to understand higher level semantics from the given input. One of the needs for AD is to provide a class for each pixel in the scene to be able to provide accurate trajectory for navigation. Semantic segmentation has gained huge attention especially after the evolution of deep learning and convolutional neural networks. Detailed literature about this topic for AD is provided in [15]. However, the impact of image degradation due to weather conditions especially soiling of the camera has not been studied on high level computer vision algorithms such as semantic segmentation which motivates us for this study in our work.

## III Methodology

In this section, we describe the challenges to implement software algorithms for visibility restoration. Afterwards, we describe our proposed methodologies to tackle them. Deep Learning is a powerful tool that can be used to restore images in poor-visibility images. However, deep learning is a data driven approach where a huge amount of data is needed to provide reasonable accuracy using CNN networks. One of the main challenges is the lack of public datasets providing paired data for clear and blinded images. The other challenge is how to use software to understand what is behind a blinded part.

### A. Towards a formal definition of Visibility Estimation

When we say visibility impairment, it means the disturbance in the cameras leading to sub-optimal image captures which might cause deterioration of functional performance of the computer vision tasks. We need to detect this obstruction as soon as it happens and come up with solutions to mitigate its effect. The visibility impairment can be caused by blockage in the camera lens due to weather conditions or image captured in sub-optimal lighting conditions such as low light or captured with motion blurs among others. Also, the impairment can be in portion of image where patch based solution can be applied or sometimes whole image can be affected where classification of the severity of impairment is needed to better act on the appropriate solutions.

### Handling Low Light

Computer vision is challenging in low light scenes as short exposure will cause noisy images and long exposure will cause blurry frames. Recent research on low light image promises huge improvements on computer vision tasks such as end to end FCN [16] used to process low light images. The network was trained with low light images and same images with normal light were used for validation to build the model to correct new low light images with exceptional performance. It is evident that the most break through deep learning research focus mostly on bright normal day light images. Not much research has been done for example to find out how good the object detection or semantic segmentation actually works in the low light images. In [17] the authors proposed exclusively dark dataset and their research found that the number of low light data should be increased during training for better low light performance because of the fact that irregular illumination is a big challenge for feature detection.

### Handling Motion Blur

In addition to weather related factors, there are other factors that cause image degradation such as noisy/blurry frames. Issue here is to estimate as well as restore an image by removing motion blur. Detecting blurry frame in not a new research topic and prior to deep learning, traditional image texture were used to detect these frames in both block/patch and image level [18]. But in [19], a sharp or non blurry image is restored by combining a pair of noisy/blurry images captured in a sequence using two neural network structures. Similarly others have used CNN to predict the probabilistic motion blur at patch level [20]. For extremely strong and spatial variant motion blur, people have used gyroscope measurements into a CNN [21] and the authors claim that this gyroscope aided motion blurring improves the performance of existing feature detectors.

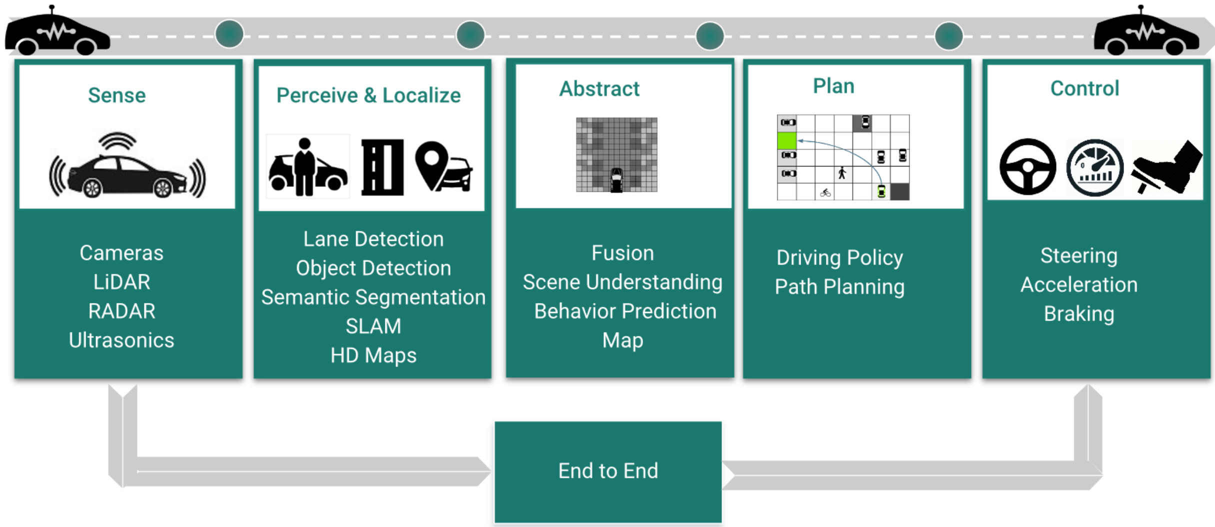


**Figure 2:** *Modules in an autonomous driving pipeline.*

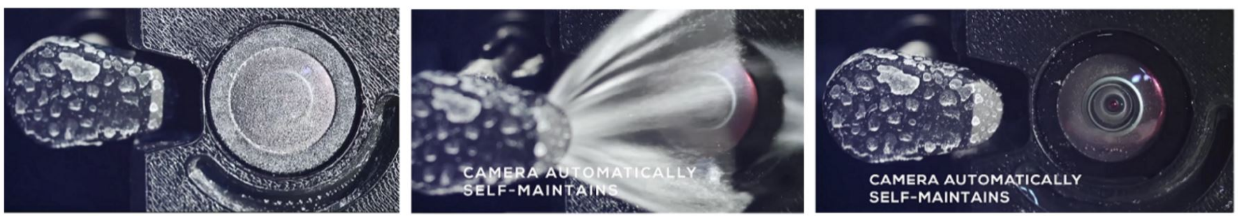


**Figure 3:** *Hardware cleaning system for blinded sensors.*

### Handling Weather Challenges

Camera sensors must continuously function across different challenging environmental conditions. The camera sensors may not produce the optimal image quality such as one with visible artifacts if the outside temperature is extremely hot or extremely cold. Moreover, camera lens could be blocked partially or fully during rain, snow or while driving off roads. In such sub-optimal situations the ADAS or AD system should continuously work as expected otherwise there will be severe safety risks. Also, if the impaired image are not corrected before using them for training, they might affect the model's performance negatively. The main environment factors that cause visibility issue are: mud, dust accumulation, water drops, ice, frost, fog and so on. To deal with some of the issues like these, we have previously developed deep neural based solutions to first detect the soiled images [22] and then restore those soiled images for improved accuracy of object detection and semantic segmentation [23].

Snow is one of the most difficult and common conditions for AD especially when detecting lanes which could be completely blocked. If there were a way to remove or reduce the snow from the image captured from the cameras before vision algorithms used them, the performance of the vision system would be much better. In [24], the authors tried to do just that by developing a multistage network named "DesnowNet" for the removal of translucent and opaque snow and were able to recover the details obscured by the snow. Similar to snow, driving in the rain is also very common practise and research has been done on removal of rain from a single image even in the presence of heavy rain. Fully convolutional network to jointly detect and remove rain from a single image has been proposed [25].

### Unifying all Visibility Estimations

Surround view cameras are becoming essential part of ADAS or AD systems but sill some of the ADAS features use single camera based feature detection such as front camera based lane detection or pedestrian detection. Use of multiple cameras for redundancy purpose not only improves the performance but also safe guards against the situation of visibility impairment due to some camera sensors. On the flip side, the amount of data to be processed increases which might be an issue in embedded platform where processing power and memory are very limited. Individual research has been done to detect and restore images with snow, rain, mud, fog, low light, motion blur and integrating them as individual DNNs is impractical. For AD all of those visibility hindrances should be tackled efficiently to make a robust system without exceeding the hardware limitations and/or cost of production. One solution for this could be using single encoder but multiple decoders as a deep neural network design. This will save huge computation power as the encoding is the most computationally heavy part of the DNN.

## B. Soiling and Restoration

**Datasets:** We propose three solutions to tackle the dataset challenge.

### WoodScape [26]

Manual Annotation for 5k images is performed by drawing polygons segmenting the blind regions, so blindness detection can be treated as a segmentation problem. The dataset is performed on fisheye images obtained from cameras installed on moving vehicles. This dataset has the advantage of providing masks for the blind areas which can be helpful in detection of the blind areas, however, the scene behind the blind area is still missing with no ground truth.

**Desoiling Dataset[23]**

Four cameras are installed on a moving vehicle capturing the front scene. Three cameras are blinded using water spray and mud intentionally and the fourth camera is kept clean for ground truth. The advantage in this dataset is that it provides the ground truth behind the blind areas. However, soiling masks still has to be done performed manually.

**GANs-based synthetic dataset[27]**

A GANs model has been used to synthesize blindness that mimics mud from harsh environment. This model has the advantages of both ground truth for the blind areas in addition to the annotation of the masked pixels.

## IV OUR RESULTS

In this section, we describe the methods we adopted to restore the real scene from blinded images.

For the purpose of environment perception in AD, embedded systems have to be able to do various tasks based on the input images such as object detection, semantic segmentation, etc. As demonstrated in Figure 1, AD cannot rely on images captured in such harsh conditions. Figure 4 illustrates the impact of directly training a well-known semantic segmentation network on blinded images due to soiled lens. In (c), it is shown that output is significantly degraded compared to (b) which is generated when the network is trained with clean images. Additionally, (g) shows the results when the network is trained on blinded images to directly predict semantic segmentation even in the blinded area using the annotation of original clean image. This results demonstrate the inability for the network to understand what is behind the scene as the model only learns the general structure of the scene including sky, road and buildings. However, it did not classify the pedestrians or the objects behind the blinded area which motivates our work for image restoration. To be able to accurately restore blinded scenes, an algorithm has to be implemented to perform two steps. First is to localize the blinded areas through and classify their type among multiple classes caused by environmental harsh conditions such as rain drops, ice, dust, mud, etc. Second is to use the masks predicted from the localization module and try to predict what is behind those areas. This will in turn be fed into the environment perception module where object detection can take place using clean images instead of the blinded ones.

In this work, we make use of GANs [28] for end-to-end image restoration. A generator is implemented to recognize which parts of the image are blinded. The network is trained to take soiled images as input and generate clean images as output. Additionally, the network is trained to accept clean images as input and generate soiled images as demonstrated in Figure 5. This method helped us to generate the dataset in [27] which help us in data augmentation for more advanced image restoration networks. To be able to generate blinded parts with variable output, MUNIT [29] has been utilized for its ability to split content from style and therefore we have control over the output masks. Another approach that we followed is utilizing temporal information. There are basically two cases that time information can beneficial for. First, when the camera sensor is blinded for some reason and the scene is static and the ego-vehicle moves in a certain direction. This way, the blinded obstacles will be seen in another visible point in the FOV, while the visible parts will be blinded. Second, when the ego-vehicle is static and the scene contains moving objects. The moving objects will keep entering and exiting the blinded area. Ideally, a combination between both situations takes place in reality. Time information can be utilized to solve these situations. For that reason, we re-define our problem as a video inpainting problem where we try to restore the image not only from the neighboring pixels but also from the neighboring images in temporally sequential frames. Figure 6 demonstrates initial results for such experiments using [30] model where it is shown that the vehicle in the middle of the image is completely blinded out and we try to restore it. The first row shows the inability to restore the car in the middle as this is the first frame in sequence. Second row shows partial restoration from neighboring frames although the object is completely blinded. Third row shows almost full restoration which shows the importance using time information for image restoration in our problem.

## V CONCLUSIONS

In this work, we discussed the problem of visibility deterioration due to harsh environment conditions. We discussed the challenges to implement software algorithms to solve the problem in terms of dataset limitations and lack of software algorithms that tackle this area. We approached our solution from both aspects providing three datasets that to encourage research in that area. We provided two baseline solutions for image restoration using GANs and video inpainting where our results demonstrate huge potential in solving such problems.

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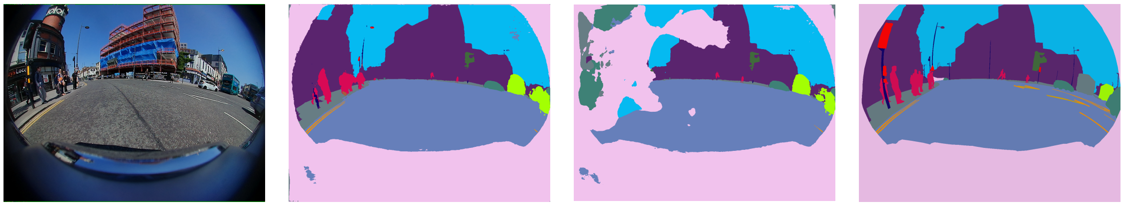

**(a)** *Clean Image* **(b)** *Train clean, test clean* **(c)** *Train clean, test soil* **(d)** *Ground Truth*

**(e)** *Soiled Image* **(f)** *Train soil, test clean* **(g)** *Train soil, test soil*

**Figure 4:** *Qualitative evaluation using clean vs soiled images on the semantic segmentation network DeepLabV3+.*


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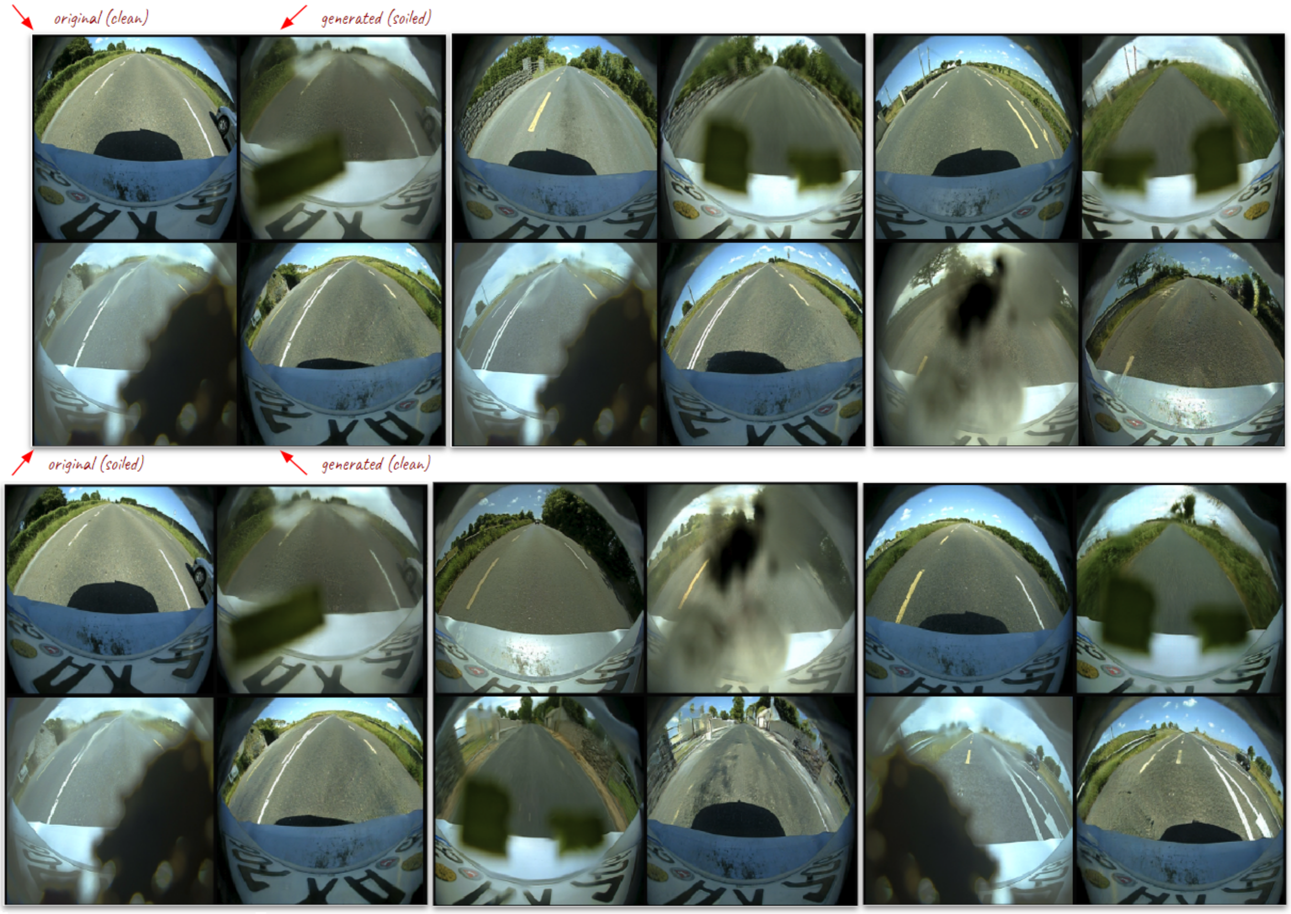


**Figure 5:** *The results obtained from the CycleGAN proof of concept for the problem of soiling and adverse weather classification. Note the legend on the first image, which is self-explanatory.*

**Figure 6:** ***Left:*** *Input Image,* ***Middle:*** *Restored Image,* ***Right:*** *Ground Truth*

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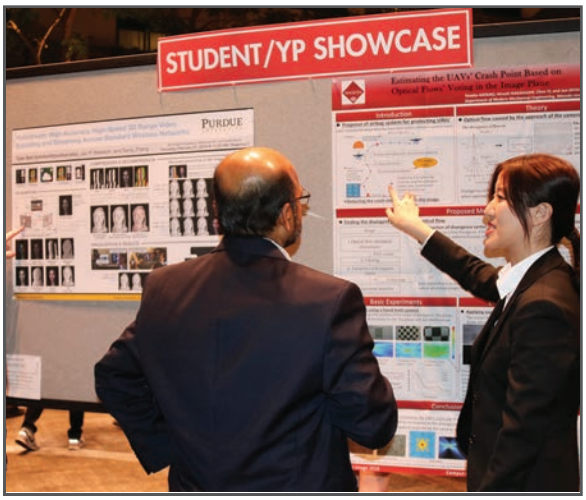


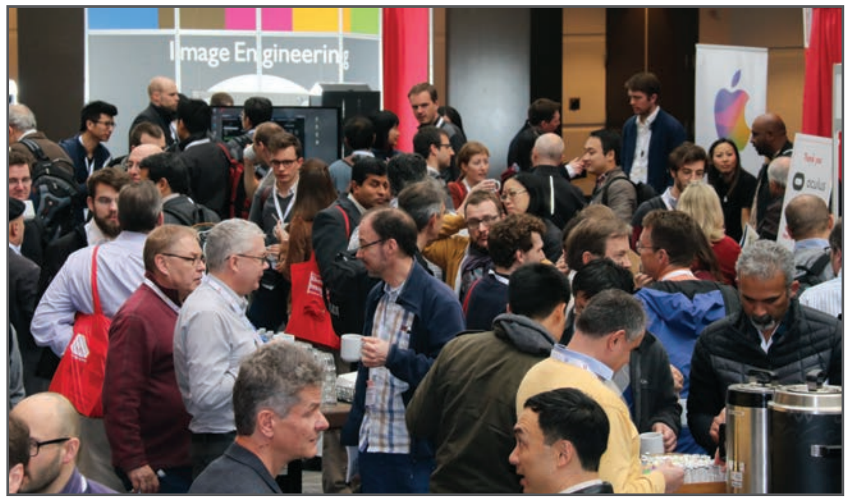


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