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IEEE-SA White Paper

IEEE P2020 Automotive Imaging White Paper

Authored by
Members of the IEEE P2020
Working Group

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IEEE P2020 Automotive Imaging White Paper

Abstract

The IEEE-SA P2020 working group on automotive imaging standards was established in order to address the considerable ambiguity in measurement of image quality of automotive imaging systems, both human and computer vision based. This white paper outlines the goals, achievements, rationale and plans of the subgroup, which has started to work on development of a new standard.[1]

Image quality plays a crucial role for both automotive viewing and automotive computer vision applications and today's image evaluation approaches do not necessarily meet the needs of such applications. Currently there is not a consistent approach within the industry to measure automotive image quality. The IEEE P2020 working group is attempting to remedy these deficiencies by connecting people in the field, identifying gaps in existing standards, and working to address these by creating a coherent set of key performance indicators by which camera systems and components may be evaluated in a manner consistent with their intended use. This white paper provides an overview of current activities including initial gap analysis and details of what may be expected from the full standard when published.

Acronyms and abbreviations

The following list of acronyms and abbreviations will be useful when reading this white paper:

ADAS	advanced driver assistance system
ADC	analog to digital converter
AEC	automatic exposure control
AI	artificial intelligence
AWB	automatic white balance
CaaS	car-as-a-service
CDP	contrast detection probability
CFA	color filter array
CMS	camera monitor system
CPIQ	camera phone image quality (as used in IEEE Std 1858-2016 [5])
CRA	chief ray angle
CSP	color separation probability
DR	dynamic range
ECU	electronic control unit

[1] For information on IEEE P2020, please visit http://sites.ieee.org/sagroups-2020/

FoV	field of view/vision
FUN	Fidelity, Usefulness, and Naturalness
GDP	gross domestic product
HDR	high dynamic range
IQ	image quality
ISP	image signal processor
JND	just noticeable differences
KPI	key performance indicators
LTM	local tone mapping
MTF	Modulation Transfer Function
OECF	Opto-Electronic Conversion Function
PWM	pulse width modulation
QE	quantum efficiency
QoE	quality of experience
RVC	rear-view camera
SAE	Society of Automotive Engineers
SNR	signal-to-noise ratio
SVS	surround-view system
VGA	video graphics array (definition of a 640 x 480 resolution display)

Overview

Telephones were once for talking, and cars were once for driving. Things have changed. Mobile phones are now ubiquitous digital assistants with cameras, sensors and extensive connectivity; while cars are on the verge of becoming multi-sensor, multi-camera, multi-modal autonomous artificial intelligence (AI) platforms. There are a number of factors that drive this dramatic evolution of our vehicles—most notably, the ability to improve safety, enable more efficient urban plans, and create new disruptive business models. The key driver for this dramatic evolution in our vehicles is to increase safety.

The World Health Organization recently noted that more than 1.25 million people worldwide die each year as a result of road traffic accidents and between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability due to their injury. This results in considerable economic losses to both individuals and their families and to nations as a whole, which equates to approximately 3% of gross domestic product (GDP) for most countries [1].

Advanced sensing will allow closer proximity inter-vehicle travel distance than human-controlled vehicles, reducing the necessary lane width and freeing up space for wider sidewalks, bike lanes, and other amenities. As cities transition away from ordinances that require large amounts of land to be used for parking and circulation, they will need to determine how best to make use of that freed-up space through new approaches of land use and zoning (American Planning Association [2]). Furthermore, the transition to autonomous vehicles brings significant opportunity in terms of new mobility business models (Gao et al. [3]). Car-as-a-service (CaaS) also will provide car mobility services for a large portion of the global population (Business Wire [4]), since no driver's license is needed, and it will prove to be an affordable transportation solution.

While cameras are crucial for a vehicle to sense and perceive its surroundings, to date there has not been a consistent approach in the automotive industry to measure image quality.

There is an existing standard for mobile phone camera image quality—IEEE Std 1858 [5]. This standard, however, is generally not applicable to automotive requirements, and additionally other image quality standards, such as EMVA1288 [6] or ISO 12233 [7], fall short for when it comes to automotive image quality use cases. Automotive imaging imposes unique challenges due to its varied and distinct landscape of imaging conditions (fish eye, multi-camera, high dynamic range (HDR), temperature range, etc.), which are not adequately addressed in existing approaches. Therefore, the IEEE P2020 working group [8] has set the goal of shaping relevant metrics and key performance indicators (KPIs) for automotive image quality, enabling customers and suppliers to efficiently define, measure, and communicate image quality of their imaging systems.

Image quality (IQ) plays a crucial role for both viewing and computer vision applications. Figure 1 shows a generic architecture of a multi-camera automotive system. In contrast to industrial machine vision systems, automotive camera systems must deal with unconstrained environments, i.e., a wide range of weather, illumination, and temperature conditions.

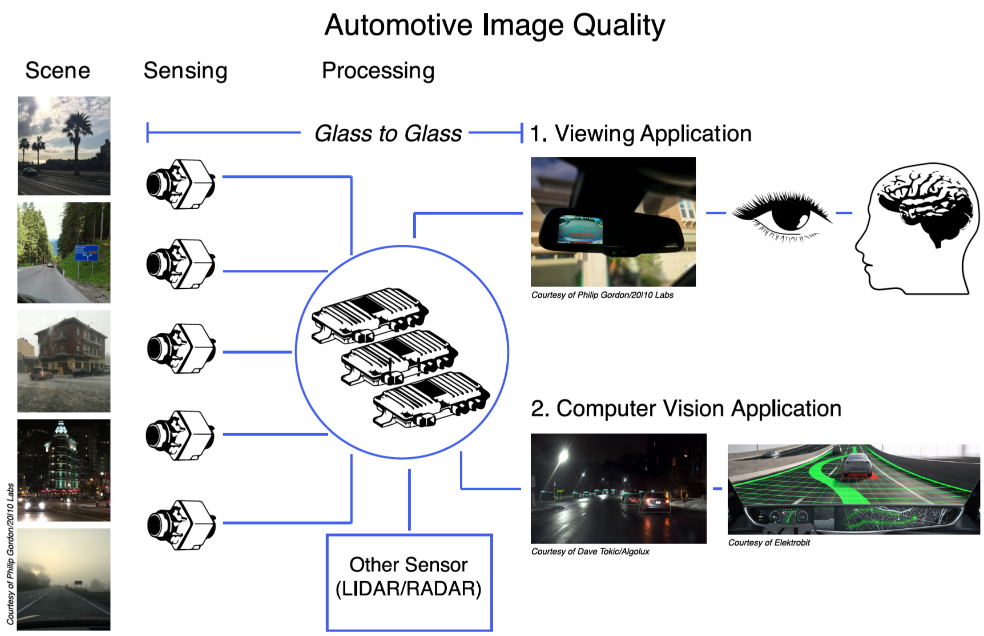

Figure 1 Architecture of multi-camera automotive system

For viewing-based camera systems (pathway 1 in Figure 1), the output image has to fulfill the pleasantness aspect of image quality, which is related to the visual appeal of the image and is a key aspect of the quality of experience (QoE) or level of satisfaction of the user. In such systems, however, the usefulness aspect of IQ, related to the amount of useful information the visual image conveys (e.g., visible detail in shadow areas), is also vital. Balancing pleasantness and usefulness is a challenge in the IQ tuning of viewing-based camera systems, since the two do not always correlate.

For computer vision-based systems (pathway 2 in Figure 1), the individual products' configuration of the hardware components [lens, image sensor, image signal processor (ISP), etc.], their parameterization, as well as the complete system IQ tuning, all have to prioritize usefulness. Here, it is important to note that biological vision and computer systems do not necessarily interpret useful information in the same manner.

Both viewing and computer vision camera systems are integral to many infotainment, driver assistance, and automated driving functions. For some of these applications, images are the primary input for the human driver or computer vision system to recognize and react to its environment. Therefore, it is extremely important that meaningful KPIs are developed to quantify and describe the performance and limits of a camera system used in such applications.

The Society of Automobile Engineers (SAE) has defined five levels of driver automation in SAE J3016 [9] with increasing levels of driving function assigned to the system, see Figure 2. These automated vehicles will use suites of sensors based on different technologies, of which camera systems are integral parts. As the automated driving systems increasingly take more responsibility for human lives, it becomes urgent to develop standard metrics to measure the performance and limits of image quality of these camera systems.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 2 SAE autonomous driving levels as defined in the standard SAE J3016 [9]

A. Goals of this white paper

This white paper is the first publication of the IEEE P2020 Working Group on Automotive Imaging. A lesson learned from the sibling group IEEE P1858 Camera Phone Image Quality (CPIQ) is that an ambitious standards development effort in a rapidly changing technological field with so many different stakeholders can take many years to be approved and published.

After our initial face-to-face meetings, it became clear that simply defining the relevant questions and listing the open challenges would already be a useful achievement worth publishing. Typically, this information would be published together with the actual IEEE P2020 standard, and would occur only after the new image quality metrics and new relevant KPIs have been defined, which may still take some time. Therefore, independent of the IEEE P2020 standard publication stage, we decided to aim for intermediate publications to quickly communicate the progress that the working group has made toward understanding automotive image quality. This white paper is the first of these publications.

Consequently, the goals of this white paper are as follows:

1) **Raise awareness that image quality for automotive application is not well-defined**, critical metrics for specification are missing, leading to repeated work efforts towards that matter. This white paper has two sections that raise the awareness about missing image quality standards. Section 1-C gives the motivation to start the IEEE P2020 effort in the first place. This includes information from the project authorization request (PAR). Section 2 introduces several problem statements; each is a summary of findings by each subgroup. In Section 3, a gap analysis of the existing image quality standards is provided. This is a list of KPIs that are relevant for automotive image quality with a reference to existing standards, and also provides an indication of the KPIs that do not have a standard (i.e., gaps in the standards landscape). Further, the existing standards are often difficult or impossible to apply in automotive applications, or they lack certain key features (e.g., in ISO 12233 [7], the evaluation of HDR is not covered). The presented list contains commentary on what elements we consider missing or incomplete.
2) **Raise awareness that the IEEE P2020 working group is trying to remedy** these deficiencies to the best extent as possible. It is time to develop a common language that customers and suppliers can use to efficiently describe automotive image quality requirements. This publication attempts to raise awareness that such an effort is under way.
3) **Connect with other people already working on similar challenges**. Because this field of technology is advancing rapidly, and due to the enormous resources pouring into the development of new camera systems for the automotive market, there are many people and organizations worldwide that are already working on many individual aspects of automotive image quality. What applies to the goal of the standard applies to the development of the standard itself—avoid duplicated efforts by connecting people working in the field and raise synergies. This white paper points out the problematic state of automotive image quality, and thus an important goal of this publication is to link together those who are already working on solutions to fill the gaps.
4) **Attract more people** to help with the IEEE P2020 effort. This white paper is also a call to attract more people and forge collaborations to help shape the future standards of automotive image quality.

B. Structure of this white paper

The rest of this section explains the motivation for the IEEE P2020 working group in more detail, the long-term objectives of IEEE P2020 as well as the current structure of the working group with its different subgroups. The actual content follows in the next two main sections:

- A problem statement by each subgroup is given in Section 2.
- A gap analysis is given in Section 3.

Section 2 describes the activity of each subgroup and formulates the challenges and missing standards in that area into a problem statement. Currently, three of the later mentioned six subgroups are active and work to define new quality metrics—subgroup 1: LED-Flicker, subgroup 2: IQ for viewing, and subgroup 3: IQ for computer vision.

The problem statements are generalized overviews of the main thrust of the work pursued by each subgroup. A more detailed list of missing metrics and lacking standards is further given in the gap analysis in Section 3, where Table 1 lists KPIs identified as important for automotive image quality. Where applicable, an existing standard is quoted. In some cases, the table already proposes new metrics to complement or replace existing KPIs. The gap analysis list is a result of collaborative discussion by the working group before and during the preparation of this white paper. We strongly hope that this list of existing standards and the indication of what is missing will be extremely valuable for anyone working in the field of automotive image quality.

C. Motivation for IEEE P2020

The IEEE P2020 Working Group on automotive imaging was inaugurated at a plenary meeting prior to the AutoSens 2016 Conference in Brussels, Belgium. The foundation of such a group arose from the needs of stakeholders in the automotive imaging community after discussing relevant industry challenges.

Since the first automotive cameras were installed on vehicles, the Original Equipment Manufacturers (OEMs[1]) and the Tier 1[2] lacked a common language for describing the quality of images in a vehicle. The Tier 1 companies were unable to exchange requirements with Tier 2 component suppliers that unambiguously reflected the aspirations of the OEMs. There were standards developed for highly-restricted aspects of some components, but the industry lacked empirically verifiable, repeatable, and commonly agreed upon descriptions for most salient aspects of the image quality of a vision system in automotive.

In the absence of a clear description of image quality, the various stakeholders independently retreated into the heuristic descriptions, to name one: “image quality is FUN” where FUN is an acronym for the Fidelity, Usefulness, and Naturalness [10]. While providing a level of image quality semantics, this is an insufficient specification. The ambiguity made projects more costly and tension in the projects more likely.

The ambiguity began with a lack of a basic description of image quality itself. While component-level descriptions of performance criteria exist, their properties were neither monotonic indicators of image quality, nor did they articulate image quality sufficiently. Examples of this include the MTF properties of lenses (using objective physical units of cycles per mm) or the disparity of a recorded color value on a ColorChecker® chart[3] (using objective physical units of Just Noticeable Differences in a color space).

After several engagements on a personal and professional level, largely facilitated by the AutoSens conference environment, a group of automotive imaging professionals formed and organized themselves into the IEEE P2020 working group.

An overview on the state of IEEE P2020 was delivered at AutoSens 2017 in Detroit on 21 May 2017 as part of the outreach work of the group in the industry [11].

D. IEEE P2020 overview and long-term objectives

The overview and long-term objectives of the IEEE P2020 standard are summarized as follows:

a) *Scope:* This standard addresses the fundamental attributes that contribute to image quality for automotive advanced driver assistance systems (ADAS) applications, as well as identifying existing metrics and other useful information relating to these attributes. It defines a standardized suite of objective and subjective test methods for measuring automotive camera image quality attributes. Further, it specifies tools and test methods to facilitate standards-based communication and comparison among OEM and Tier 1 system integrators and component vendors regarding automotive image quality.

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[1] Original Equipment Manufacturers—the automobile companies.

[2] A Tier 1 company is one that supplies components directly to the original equipment manufacturer (OEM) in the supply chain. A Tier n+1 company supplies a Tier n company in a supply chain.

[3] ColorChecker is a registered trademark by X-Rite.

b) *Purpose:* This standard specifies methods and metrics for measuring and testing automotive image quality to ensure consistency and create cross-industry reference points.

c) *Need for the project:* Cameras are being used in greater numbers in automotive applications. Most of these systems have been developed independently, with no standardized calibration or measurement of image quality. Consumers have no standard reference point when using camera-embedded systems, and OEM or Tier 1 developers cannot compare camera systems side by side.

d) *Stakeholders for the standard:* Automotive OEMs, Automotive Tier 1 suppliers, image processing software and hardware companies, optics companies, sensor manufacturers, safety certification bodies, end users (drivers).

E. Subgroups

The various subgroups formed within the IEEE P2020 Working group are described below. An overview of the projects is depicted in Figure 3.

- Subgroup 0—Image quality requirements/specifications standards
- Subgroup 1—LED flicker standards
- Subgroup 2—Image quality for viewing
- Subgroup 3—Image quality for computer vision
- Subgroup 4—Camera subsystem interface
- Subgroup 5—Image quality safety
- Subgroup 6—Customer perception of image quality

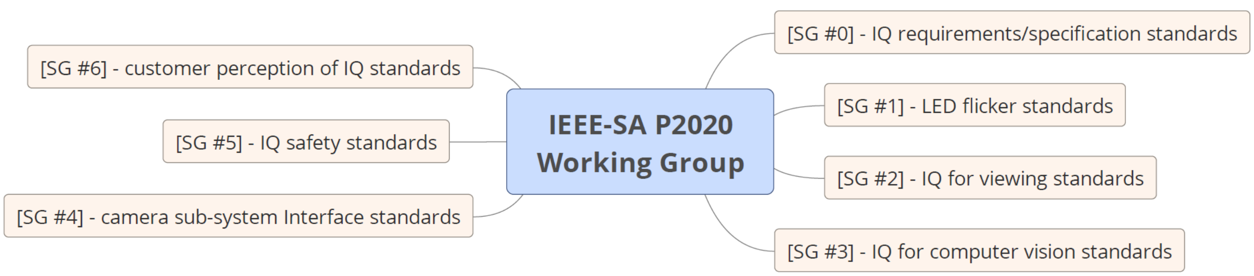


Figure 3 IEEE-SA P2020 subgroups overview

2. Problem statement

This section describes the findings by the active Subgroups 1, 2, and 3.

A. Subgroup 1—LED flicker standards

1) Motivation: LED flicker is an artifact observed in digital imaging where a light source or a region of an imaged scene appears to flicker. The light as observed on the vision system display may appear to switch on and off or modulate in terms of brightness or color, even though the light source itself appears constant to a human observer. An example of LED flicker is shown in Figure 4.

Frame N Frame N+1

NOTE—The images above show two consecutive frames from a video sequence. In frame N, the traffic light in the front (highlighted in red dashed circle) appears with red light on. However, in frame N+1, the traffic light in the front, which is still visually observed by a human as a red light on, is no longer captured by the camera, thus leading all lights of the traffic light to appear off.

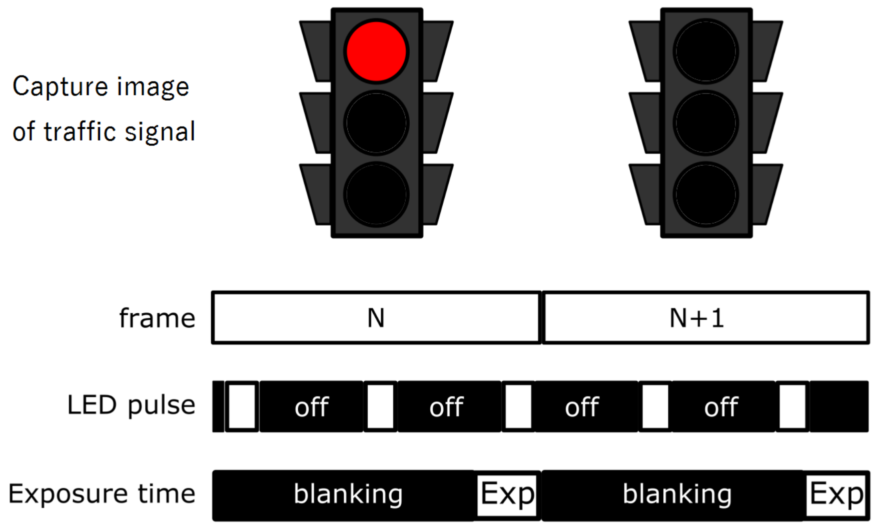
Figure 4 Example of LED flicker[4]

LED flicker is, in essence, a temporal/spatial sampling problem. It occurs when a light source is being powered by a pulse width modulated (PWM) signal. LED lights may pulse several hundred times a second with varying duty cycle (i.e. the fraction of one period when the light is active) in order to adjust their apparent brightness. At frequencies greater than 90 Hz, the light will usually appear to be constant to most human observers. A camera capturing the pulsed light source, however, may require a shorter exposure time than the temporal “ON ”period of the PWM signal to prevent overexposure of the image, particularly in bright ambient light conditions. An illustrative example of the timing phase mismatch that causes missing exposure is shown in Figure 5 [12].

2) Impact of LED Flicker: The implications of PWM flicker vary depending on the application. For simpler viewing applications (e.g., a rear view park assist camera), LED flicker may be considered as an annoyance or at worst a distraction for the driver. There is, however, a risk that LED flicker may trigger seizures in people with photosensitive epilepsy. For a camera monitor system (CMS: a system that may optionally replace a conventional vehicle mirror), flickering headlamps may be mistaken for turn signals and indicators or, as has been reported, may cause the driver to misidentify a following vehicle as an emergency vehicle.

Flickering may also occur when a scene is predominantly illuminated by a pulsed light source. In this use case, a large area or the entire image area may be affected. A typical example is a scene that is illuminated by a vehicle headlamp or streetlight, which is driven by a pulsed signal. The flicker artifact has both temporal and spatial characteristics. For example, if a rolling shutter image sensor is used, banding artifacts may occur, i.e., dark bands across the image. An illustrative example of banding effect is shown in Figure 6. If global shutter read-out architecture is used, the image brightness will vary from frame to frame.

[4] Figures are modified from [12], reprinted with permission of IS&T: The Society for Imaging Science and Technology sole copyright owners of *Electronic Imaging, Autonomous Vehicles and Machine 2018.*



NOTE—In frame N, the LED pulse and the camera exposure time coincide, and the traffic light is captured. In frame N+1, the LED pulse and exposure time do not coincide, and the traffic light appears off.

Figure 5 LED flicker root cause[5]

NOTE—This image was captured with a rolling shutter image sensor. In this example, the scene is illuminated by a diffuse LED light source, driven by a 75Hz, 10% duty cycle signal. The image shows a typical banding effect with darker horizontal stripes, representing the rows missing the exposure of LED illumination ON timing.

Figure 6 Example of banding artifact[5]

[5] Figure is a modified from [12], reprinted with permission of IS&T: The Society for Imaging Science and Technology sole copyright owners of *Electronic Imaging, Autonomous Vehicles and Machine 2018.*

For computer vision-based ADAS or autonomous driving applications, the consequences may be more severe. LED flicker may cause misidentification of traffic signals, speed signs, or safety messages. It should also be noted that LED flicker can adversely affect automatic exposure (AE) algorithms, causing oscillations in overall image brightness. The goals of subgroup 1 are as follows:

- Document the root cause and manifestations of flicker.
- Capture use cases and potential impact of flicker.
- Define standard test methodologies and KPIs for flicker effect measurement. Note that the KPIs and test metrics are intended to be applicable for black box testing as system.
- Correlate objective flicker metrics with subjective (visual) experience of flicker.
- Correlate objective flicker metrics with computer vision performance.

B. Subgroup 2—Image quality for viewing

1) Motivation: Subgroup 2 on image quality for viewing will be engaged in developing meaningful KPIs to characterize image quality for automotive cameras including rear-view cameras (RVC), camera monitor systems (CMS), and surround view systems (SVS) and their components such as lens, color filter array (CFA), sensor, image signal processors (ISP), and displays. The complete imaging chain (glass to glass, see Figure 1) is to be covered and a preliminary approach is to measure the signal prior to the display, assuming a reference display and viewing setup to be defined and applicable (display size, viewing distance, environmental illumination, etc.). A bottom up approach is used to design metrics on the component level first and derive system performance as concatenation of multiple components, thus benefiting from component level KPIs.

2) Problem statement: The image quality requirements for viewing application can hardly converge into a single setup if different use cases are considered. Further needs to co-exist with the emerging computer vision application make this problem even more difficult, imposing conflicting goals.

For example, even within purely viewing-based systems, the users will judge the image by two contradicting judgements: By its usefulness (e.g., displayed details) as well as visual aesthetics (e.g., less noise). Different image quality aspects contribute to a pleasing image but may conflict with one another, e.g., noise vs. brightness vs. sharpness vs. texture vs. color saturation. Figure 7 shows an example of how an image could look according to different capture settings and/or processing.

In the context of automotive imaging, image quality KPIs for viewing need to be able to meet these competing aims simultaneously. This is challenging and it may largely depend on the task performed by a driver viewing the images provided by the camera visual system.

Automotive IQ KPIs need to reflect such conflicting goals of the images' use.

NOTE—Images (a) and (b) demonstrate an example of trade-offs between image usefulness and visual aesthetics. Both are night images of the same scene that were captured using two compatible camera modules in HDR mode but with different operation settings. While one may observe more details and, therefore, be able to better distinguish between the objects in image (a), image (b) taken with different settings provides a more pleasant image thanks to lower noise levels and a higher contrast between bright and dark objects. For comparative purposes, images (c) and (d) show a crop of the central region of images (a) and (b) respectively.

Figure 7 Tradeoff example

There are a number of major challenges to incorporate current image quality standards in an automotive environment, such as the following:

- **Fish eye lens, focus, resolution**—The use of fish eye lenses with wide angular field of view and fixed focus, combined with relative low resolution image sensors imposes specific challenges. In these scenarios, typical test chart sizes and setups are too small, resulting in images without a sufficient number of pixels for robust analysis. Decreasing the distance between test chart and camera introduces new problems. On the one hand, if the chart is positioned at a distance to cover the entire image area, that distance may become shorter than the camera designed depth of field and result in a blurred image. On the other hand, fish eye lenses usually suffer from lens distortion. This introduces other problems (failure of the charts' patch automated detection with existing tools, distorted patch sizes at different locations within the image, etc.). Simply increasing the test chart size will not solve the problem and introduces other challenges, e.g., achieving a uniform illumination over the entire charts area that are often required for most image quality standard evaluation procedures.

- **HDR**—High dynamic range imagers are often combined with local tone mapping image processing. This creates challenges of texture and local contrast preservation, color fidelity/stability, SNR stability (see Figure 8), and motion artefacts.
- **Multi-cam**—In applications such as SVS, image capture originating from multiple cameras with overlapping field of views are combined or "stitched" together. The created virtual image evaluation is problematic due to the individual characteristics of each camera and captured portion of the scene, i.e., different fields of view, local processing, different and mixed camera illumination.
- **Distributed**—Distributed systems with some local image processing close to the imager and some ECU centralized processing. Local processing (e.g., tone mapping) does not preserve the original information at the camera and is therefore not invertible to be post recovered in the central ECU (e.g., glossy compression/quantization).
- **Dual purpose**—The same camera feed may have to serve both for viewing and computer vision needs.
- **Extrinsic components**—System level image quality is affected by additional components of the vehicle (lights, windshield, protection cover window, etc.).
- **Video**—Automotive systems use video imagery. Many of current imaging standards, however, were originally targeted for still image application and typically do not cover motion video image quality.
- **Illumination**—The huge variety of the scene illumination in automotive use cases imposes additional challenges for testing (e.g., xenon light, d65 light, sunlight, various LED street lamps).

Another issue is that the existing standards do not necessarily cover the specific challenges that occur in uncontrolled use environments, in which automotive camera applications need to operate.

Figure 8 shows a typical SNR versus illumination curve of camera using a multi-exposure type of HDR operation. When a high dynamic range scene (e.g., tunnel entrance/exit) is captured, a counterintuitive phenomenon may occur in regions of the image above the intermediate SNR drop point. Brighter regions above those drops will exhibit higher noise than regions with a lower brightness. This means that there is more noise in the intermediate bright regions than in the dark ones. In the case where an application requires a certain minimum level of SNR, these intermediate drops become an issue because existing standards on HDR do not consider such intermediate SNR drops. Figure 8 illustrates an example SNR curve of a sensor operated in an optimized configuration to achieve improved SNR at these drop points. This consequently leads to reduced dynamic range from 144 dB down to 120 dB, according to operation adjustment required to achieve an improved overall SNR level.

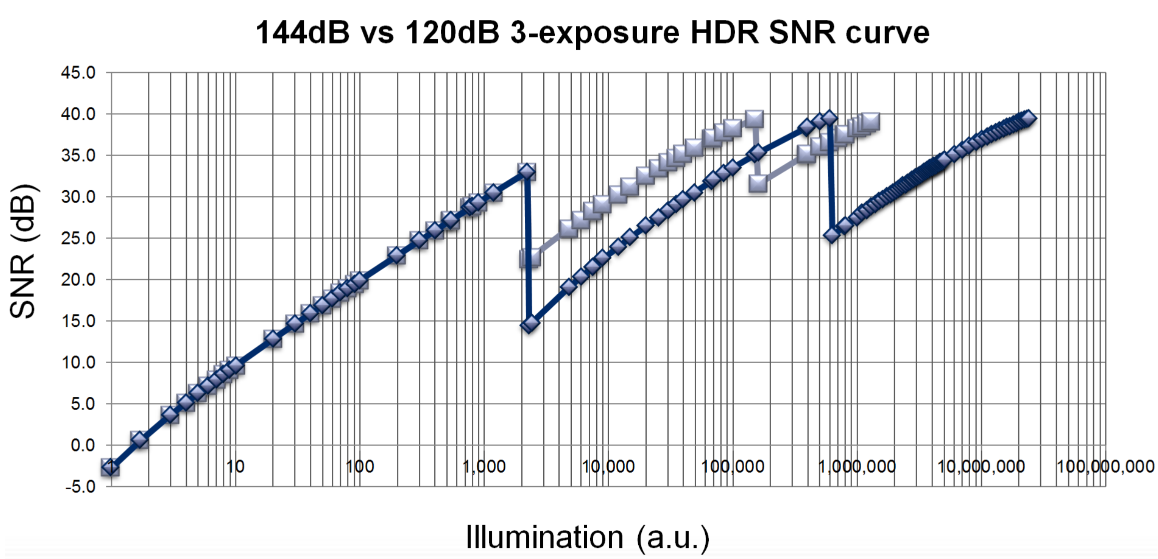
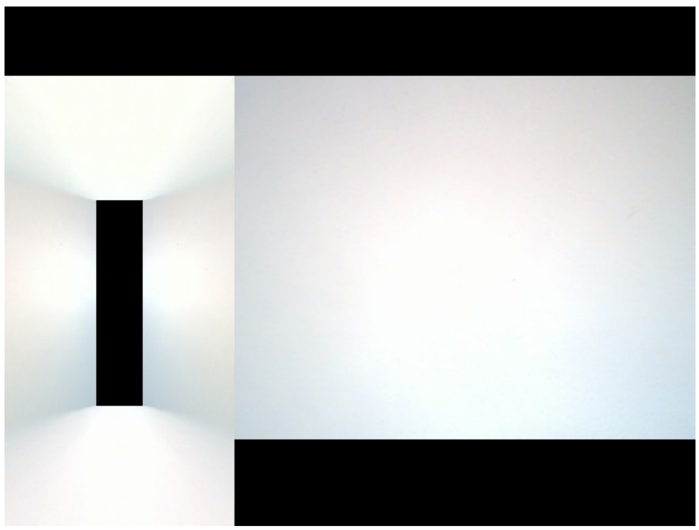


Figure 8 SNR vs. illumination for multi exposure HDR imagers

SNR spatial drop within an image may also be observed in camera using wide angular field of view fish eye lenses. Typically, cameras with a wide FoV lens have a high degree of lens shading, which means the signal drops radially, in some case to a level lower than 50%. If we consider a SVS where typically four different wide field of view camera images are processed to generate a virtual bird's eye view image from above a vehicle, brightness correction is performed to compensate for the darker peripheral image (as in image shown in Figure 9). The lens shading correction is applied to mitigate the bordering effect of the image coming from different cameras, which in turn leads to an inhomogeneity in the SNR as higher gain is applied to the peripheral area of the fish eye lens. This non-uniform, spatially varying effect gets extremely prominent, especially for a multi-camera combined SVS. The higher the gain to compensate for the lens shading at the peripheral area of the images causes the borders of the stitching areas to generate a large step of visible noise, in some case to a perceivable level when observing these images.



NOTE—The left side image is a combination of a left, front, right, and rear mounted camera image to create a virtual top view image in a SVS image. The right side image is native image of rear camera to provide view corresponding to a RVC image. All images from cameras are capturing a near uniformly illuminated white flat chart. In the right side, one can observe a signal drop toward the periphery, and the left side, one can observe steps in the signal along the merging stitching lines along of neighboring camera in a SVS view.

Figure 9 Brightness inhomogeneity due to lens shading in a combined multi-camera view

Typically, in the existing IQ standards, one major requirement prior to the calculation of a metric is the linearization of output values. This involves the calculation of the Opto-Electronic Conversion Function (OECF) and correction of any system non-linearity accordingly. The typical automotive camera system with HDR and Local Tone Mapping is a nonlinear system. The linearization of the input signal under strictly controlled parameters is still possible, but in a typical automotive application use case, e.g., in scenes with high dynamic range, the same conventional linearization procedure cannot be used anymore. As many KPI are calculated assuming a linear relationship of the output signal, the unavailability of OECF has a significant impact on the calculation of several conventional IQ standards such as sharpness, noise texture, etc.

Furthermore, due to the high dynamic range of the imager, technical challenges arise for the optical design of the lenses. Repeated reflections of the light inside the lens will lead to ghost images such as the headlights of a car. As we use a HDR sensor combined with LTM (local tone mapping), the ghost image of the headlights will be amplified to a significant level at dark region of the same captured image. For CMS camera systems, this will lead to two to three pairs of headlights in the actual image, which can be misguiding for the driver. Unfortunately, the higher the imager DR and LTM performance, the more serious these ghosting problems will become.

A number of challenges arise when using the texture measurement metric in automotive applications (used by CPIQ), which is based on the dead leaves test chart. Again, the wide FoV and low resolution will not provide enough pixel counts for a robust and reliable measurement. Decreasing the distance or increasing the target size will distort the well-defined frequency distribution and geometrical invariances of the dead leaves within the test chart due to the high lens distortion. Typically, low texture KPI values are caused by high noise reduction filtering in the image. However, if we now have an image where the SNR is not a continuous function of the illumination due to the SNR drops, and the noise reduction filtering is hence not necessarily done equally over the whole image, then we have to ask: How much can we benefit from the measuring method as presently described in the CPIQ standard?

Given the multitude of use cases and complexity to achieve good KPIs, subgroup 2 has decided to first work on development of the following ease implementation ones, in a bottom up approach, before further moving to complex KPIs:

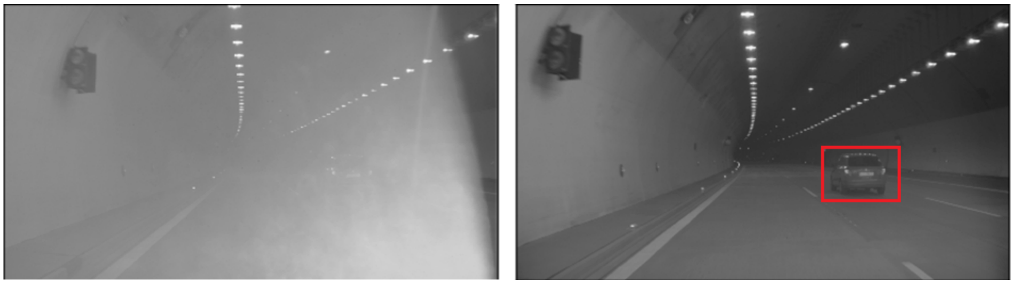
- Dynamic range
- Sensitivity
- Depth of field
- Focus stability
- Dark current

Our ultimate goal is to design KPIs to characterize image quality with regard to both the pleasantness and usefulness to the automotive viewing camera systems; and will further tackle new KPIs at next stage.

C. Subgroup 3—Image quality for computer vision

1) Motivation: Video-based environment recognition is expected to be one of the major components of an advanced driver assist system (ADAS) or automated driving system. The process of environmental visual data acquisition is the result of a complex effect chain, also called imaging chain, which starts from a light source and ends with the final image stored in memory. In this information transfer chain, the signal suffers from a variety of intermediate disturbances, thus degradation of the signal quality will always take place to some extent. It is important that the system is designed so that enough relevant information about the world is still preserved in the chain. Hence, it is evident that meaningful KPIs need to be defined. Because the tasks of computer vision are so diverse and are solved in many and constantly evolving ways, existing standards such as EMVA 1288 [6], are typically restricted to component-level characterization. However, to cover special automotive use cases, the complete system along the imaging chain has to be considered. Existing international standards for image quality, while application based, almost exclusively focus on the case of digital imaging for human consumption. The machine vision use cases of automotive imaging are so diverse, and the penalty for failure so severe in critical cases, that existing standards are inadequate for computer vision automotive application. What might lead to merely acceptable image quality degradation for human consumption may lead to sudden unacceptable failure for a computer vision system.

As an example, consider the scenario illustrated in Figure 10, wherein a vehicle passes from being in direct sunlight into a tunnel. The vehicle has a dirty windshield and the forward-facing camera is essentially blinded by veiling glare introduced at the surface by haze and/or reflections. Thus, the distinguishability of the scene feature (i.e., the car) is vastly reduced. The car becomes clearly visible once the vehicle windshield enters the tunnel and the veiling glare is not present anymore. A situation such as dirt on the windscreen will drastically reduce the detection probability of the relevant object (e.g., a car), regardless of the specifics of the system analyzing the video feed. Intelligent driving systems that make use of these video feeds and other sensors modalities are not allowed to fail in such cases. Therefore, it is vital to provide these systems with all the necessary information from the environment in order to make proper decisions.



NOTE—Two sequential video frames while entering a tunnel that demonstrate contrast reduction by veiling glare, caused by sunlight illuminated dust particles. In the left image, the effect significantly hinders the recognition of a preceding car while in the right image (only a few milliseconds later) the sunlight is blocked away and a robust detection of the car is possible.

Figure 10 Two sequential video frames while entering a tunnel that demonstrate contrast reduction by veiling glare[6]

2) Problem statement: Traditionally, the evaluation and characterization of components in the imaging chain were covered by specific expertise in the field of each component. For example, optics KPIs such as Modulation Transfer Function (MTF) and such as the quantization of various effects of scattered light in the optical system are not directly compatible with image sensor KPIs like signal-to-noise (SNR) and dynamic range (DR). The overlapping effects between components often do not have a common unified evaluation standard across the component chain. Following the example in Figure 10, a standard approach might have been to quantify how much veiling glare a dirty windshield adds to such an imaging situation, and for the vision system designers to account for this in their design, whatever the application might be.

Thus, the definition of the components requirements for an ADAS system is a complex procedure. A particular effect observed in the intermediate data flow is not necessarily isolated and it requires a complex analysis of the complete information transfer flow. This means it is necessary to analyze the chain from optical level down to electronic signal level (see Figure 11), and this must be done considering the use cases in which the system is expected to operate. Therefore, it is essential that components are not just characterized as isolated elements but rather all effects in the chain are well covered under a single framework so that the total system can be appropriately characterized.

Given the example of Figure 10, the reduced contrast after the windshield could still be detected by an image sensor with sufficient contrast detection ability and consequently the ISP may reconstruct an image that allows detecting the car even in the left hand side image with a still sufficient detection probability.

[6] Figure from [13] reprinted with permission of IS&T: The Society for Imaging Science and Technology sole copyright owners of *Electronic Imaging, Autonomous Vehicles and Machine 2018*.

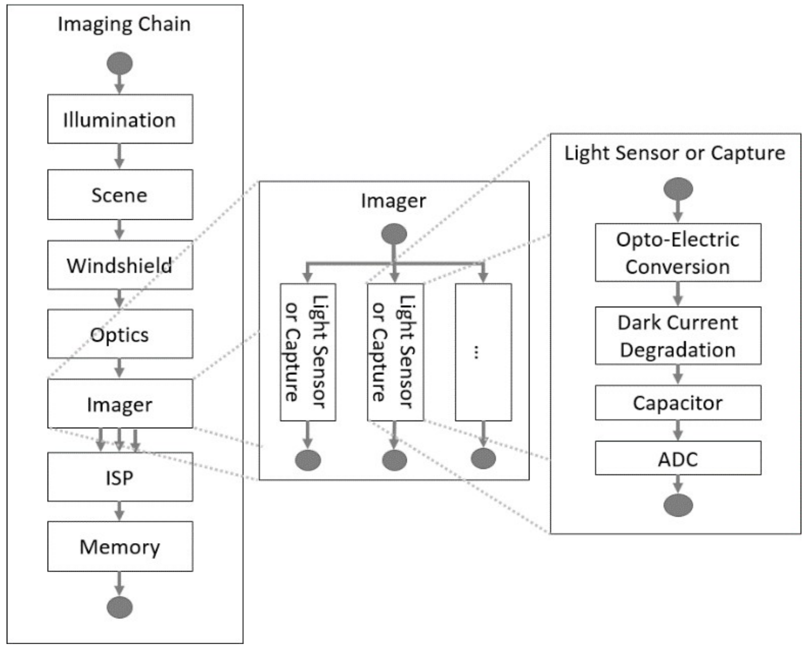


Figure 11 Example flow diagram of an imaging chain[6]

In order to design robust systems for the automotive industry, IEEE P2020 subgroup 3 (Image Quality for Computer Vision on System and Component Level) aims to develop consistent metrics that both describe various degradations and give bounds on their confidence. We will explore the probabilistic approach of distinguishability, such as the contrast detection probability (CDP). This helps to visualize the overall signal chain and aims to improve the cross domain barrier. CDP is a metric designed to specifically measure this fundamental aspect, using a framework well founded in theory (Geese et al. [13]). Moreover, CDP has the ability to be applied to each element of the imaging system chain, so that the original task can be described at each step in the imaging chain.

3) Outlook and Conclusion: Within the discussions, subgroup 3 gave awareness for new top-level image quality KPIs for automotive computer vision applications. In a first approach, these new top-level KPIs will be based on the principle of detection probabilities. As the first of these new probabilistic KPIs, the Contrast Detection Probability [13] is already defined in the scientific community; IEEE P2020 will adapt this definition into a first proposal by the end of 2018. Here, a validation of this CDP approach with exemplary cameras will be demonstrated in laboratory test environments by members of the working group. For the distinguishability of traffic-relevant colors, the discussion of a probabilistic approach has already begun in analogy to the principles of CDP and is referred to as color separation probability (CSP). A further important domain of image quality is the geometric resolution that will follow with high priority. For all definitions and KPIs, subgroup 3 plans to contribute an example implementation to verify and develop the newly defined KPIs against the currently established KPIs, while a laboratory validation is intended to follow as described above.

3. Gap analysis

Because automotive imaging is quite unique with regards to hardware setup and customer functions, it became clear that existing image quality KPI standards are not sufficient to address such systems. Table 1 exemplarily depicts some obvious gaps. The goal is to identify the attributes within the relevant environmental conditions that affect the image quality of automotive systems and subsequently define universal methods to quantify them.

Table 1 Gap analysis

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
Tonal response	**Dynamic range**	ISO 15739: 2017 [14], EMVA 1288 [6]	Evaluation on monotonical response input image. Given as the ratio of the signal saturation to the absolute sensitivity threshold	Dynamic range definition on multi-exposure type of sensor; dynamic range of displayed imaged with adaptive tone mapping; dynamic range considering a minimum SNR required over its defined range. (A minimum SNR required to perform intended operation, e.g., distinguishing an object.)	Window glare, optics flare, sensor intrinsic dynamic range and quantization, compression I/F	Sensor
	Contrast Detection Probability (Dynamic range that meets specific CDP)	New approach in IEEE P2020	—	Gap to close: Define the dynamic range and other dependencies, where the signal allows the detection of a certain Object Category (feature: Contrast) for the targeted application. For more details, see literature [13]. For example, guarantee detection even if SNR drops are present in multi-capture systems.	—	System and Component Level
	Sensitivity	ISO 12232 [7], Speed; EMVA 1288 [6], QE	Digital Still Camera, Visual spectrum	Definition extend to IR spectrum.	—	Sensor
	Low light performance	ISO 19093 [15] (in development)	Smartphone camera evaluation is main focus of this standard	Low light performance on actual use condition, definition considering trade-off operation according to application (2D, 3D NR operation dependence on scene brightness, ...).	SNR, Temperature dependency, NR operation	Sensor
	SNR 1/5/10	—	Illuminance in lux that delivers image with at least the defined SNR value equal to 1, 5, or 10 for a neutral grey patch.	Alternative to low light performance.	—	Sensor
	Tonal shading	ISO 17957 [16]	Metrics defined using a flat target chart	Needs adaptation to wide view angle application.	Optical, CRA	Sensor
	Chroma shading	ISO 17957 [16]	Metrics defined using a flat target chart	Needs adaptation to wide view angle application.	Optical, opto-device, device cross-talk	Sensor
	OECF	ISO 14524 [17]	OECF (Evaluation on monotonical response input image)	Evaluation on adaptive tone mapping operation.	—	Sensor

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
Spatial response	**Resolution**	ISO 12233: 2017 [7]	Units given relative to image full dimension/optical definition	Definition required according to intended use FoV; Metric to evaluate scene distinguishability performance; Partial/converted image resolution from a fish eye lens. (Example: CMS where output image evaluation is based on displayed image instead of camera intermediate image).	—	Optics
	Limit resolution	(can be derived from ISO 12233: 2017 [7])	Defined according to required use case	For automotive visual application, object in the range of interest must be distinguishable. The spatial frequency where MTF drops to 10%, or MTF10, is adopted for automotive visual application as representative characterization value, e.g., CMS applications.	—	Optics
	Sharpness	(can be derived from ISO 12233: 2017 [7])	—	The peripheral vision plays an important role in the first stage of visual detectability of object and it is known that the edge contrast stimulates the peripheral vision. The spatial frequency where MTF drops to 50%, or MTF50, is adopted for automotive visual application as representative characterization value.	—	Optics
	Depth of field	—	—	There are industry practices to measure depth of field/focus, but no standard exists based on object distance and MTF requirements. In principal, one may expect a camera to be assembled in hyper-focal distance with good focus achieved in a range from half of the hyper-focal range to infinity, if otherwise not mentioned.	—	Optics
	Texture	ISO 19567-1 [18], ISO 19567-2 [19]	Low distortion image to maintain chart spatial frequency characteristics			Optics
	Motion Blur (Single exposure tail, Multi exposure Ghost in HDR single frame)	No existing standard		This item is more an intrinsic effect due to the exposure time used to capture a frame image.	Sensitivity, Electronic Shutter operation	various
Temporal response	**Flicker** (observed undulation effect) (Focal Plane Shut-	No standard for camera operation,	(Temporal to spatial transformation due to time-sequential	Need to cover the emerging use of LED light source, which nowadays largely used in many road environments (including reflected scene illuminated by such type of	—	Sensor

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
	ter) at low to middle range scene luminance	Standard defined only for light source	sampling characteristic of the focal plane shutter sensor operation)	source) Intra/Inter-frame static, semi-static, moving undulation.		
	Flicker (observed flickering effect) (FPS & HDR w/Local Tone Mapping: LTM)	No standard for camera operation, but as light source	(HDR operation used to cover for the highlight are affected by the adaptive tone mapping and/or further time sequential multi sampling , and its multi-frame merging signal process, creating non-linear artefacts)	Need to cover the emerging use of LED light source in road environment (traffic sign, headlamp, tail lamp, traffic signs, etc.)	Localized (point) light source	Sensor
	Flicker (Global Shutter)	No standard for camera operation, but as light source		Need to cover the emerging LED light source used in road environments, parking, etc.	—	Sensor
Spectral response	**Spectral Quantum Efficiency**	EMVA 1288 [6]	—	—	—	Sensor
	Color Rendering	—	—	Automotive scene may contain scene illuminated under a variety of different light source. Also light source captured as part of the scene may largely differ from the scene illumination. Compared to post adjustable use case of photographic application like DSC or post processed video application, a precise color rendering is not expected to be achievable.	—	Variable
	Distinguishability of traffic relevant color	—	—	Although a precise color rendering is not applicable or feasible, the extent of color deviation shall be such that traffic relevant colors are still distinguishable within same color classification range. Red as red, green as green, amber as amber.	Distinguishability of traffic relevant light source colors	Various

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
Optical artifact	**Lens flare**	ISO 18844 [20], IEC 62676-5 [21]	—	In automotive use environment, headlamps direct light and/or direct sun light often enters the FoV or hit the optics of the camera system. Stray light of incident light onto optical system shall be evaluated in term of veiling effect that deteriorate image visual or post processing performance.	Distinguishability of target objects affect by flare	Optics
	Ghost	—	Secondary image of primary light source created by stray light reflected within the optical components		—	Optics
	Veiling glare	ISO 9358 [22]	Stray light that reduces the image or display contrast over a significant area of the total image or display area	—	Lens flare, distinguishability of objects affected by flare	Optics
	Lens color aberration	ISO 19084 [23]	—	—	—	Optics
	Stray light	—	Stray light is a general term that refers to light affecting the image quality that is unintended by the optical system.	—	—	Optics
Noise	**SNR**	ISO 15739:2013 [14]	—	Noise reduction operation is largely adopted in camera systems, but may result in spatial resolution degradation. Therefore, for the comparative evaluation of system, measuring operation condition shall be defined in accordance. HDR operation suffers the degradation of SNR in intermediate brightness rather than at low light condition.	—	Sensor
	Read-out noise	EMVA 1288 [6]	—		—	Sensor
	Temporal noise	ISO 15739: 2013 [14],	Temporal Read Noise is the time-dependent	—	—	Sensor

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
		EMVA 1288 [6]	fluctuation in the pixel signal level			
	Color noise	ISO 15739: 2017 [14]	—	—	—	Sensor
	Fixed-temporal noise	ISO 15739: 2017 [14], EMVA 1288 [6]	—	—	—	Sensor
Non-uniformity	**Tonal Shading**	ISO 17957 [16]	Flat Chart and visual spectrum	Wide view angle needs not covered.		Various
	Chroma Shading	ISO 17957 [16]	Flat Chart and visual spectrum	Wide view angle needs not covered.		Various
	Photo Response non uniformity (PRNU)	EMVA 1288 [6]				Sensor
Thermal performance	**SNR degradation** at high temperature	—	Dark leak current is one of main noise source at high temperature and doubles about every 10 °C	Some application requires high temperature operation.	—	Sensor
	Resolution (drop at high temperature)	—	—	Exposed to wide temperature variation with fixed focus as assembled.	—	Optics
	Color effects at high temperature	—	—	Dark level off-set deviation, gain deviation.	—	Sensor
Functional performance	**Automatic exposure control**	—	—	Exposure accuracy, tractability, start-up delays, hysteresis properties, others.	—	ISP/Proc.
	Automatic white balance (AWB) control	—	—	White balance light source detection accuracy, tractability, start-up delays, hysteresis properties, others.	—	ISP/Proc.
System-	**Inter-camera image**	—	Image continuity in merging border	—	—	ISP/Proc.

Technical category	Item	Existing industry standards	Original use case of existing standard, or comments	Gap to automotive particular needs	Correlated Item, comments	Cat.
based requirement (Multi-camera system like SVS)	**(geometrical and timing mismatch)**		between different camera images. (Adjustment capability, range of adjustment, countermeasures, etc.)			
	Inter-camera image (exposure mismatch)	—	Image continuity in merging border between different camera images. (Adjustment capability, range of adjustment, countermeasures, etc.)	—	—	—
	Inter-camera image (White Balance mismatch)	—	Image continuity in merging border between different camera images. (Adjustment capability, range of adjustment, countermeasures, etc.)	—	—	—
Others	**Lens distortion**	ISO 17850 [24]	Evaluation as camera capture image	Distortion on intended viewing orientation (cropped image from fish eye lens with intended view projection correction).	—	—
	HDR multi-exposure artefacts	—	—	Colored or edged ghost on moving object edges due to sequential exposure delay.	—	ISP/Proc.
	HDR multi-exposure tonal reproduction	—	—	The tonal reproduction of HDR image is neither monotonically increasing nor linear to incident light, and it is also largely affected by scene content.	—	ISP/Proc.

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