Supplemental material for CVPR23 WAD Paper Joint Camera and LiDAR Risk Analysis

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Table 1 includes data characteristics and specification of autonomous driving datasets with camera and LiDAR data. Table 2 contains the full list of LiDAR HAZOP entries. HIDs are identical to the connected camera risk HID from the generic CV-HAZOP [15] as well as the specialized stereo vision version [14]. The *Observer* location has been renamed to *Receiver* for easier readability. The location *Light Sources* (L. S.) is split into two locations for the LiDAR HAZOP: *Emitter* and (other) *Light Sources*. The HID for *Emitter* location entries get appended by the letter *e*. Entries for the newly introduced *Receiver* parameters (local & global registration) have no connected CV-HAZOP entry and use new HIDs starting with HID 3000. Table 1. LiDAR datasets for autonomous driving. (---) indicates that no information is provided.

DATASET NAME	YEAR	TYPE OF DATA	NUMBER OF SCENES / VARIABILITY	VIDEO FEATURES (NUMBER OF FRAMES / FRAME RATE (fps))	LiDAR FEATURES (FRAME RATE (Hz) / NUMBER OF BEAMS / ACCURACY (cm) / RANGE (m))	FEATURES	ANNOTATIONS
KITTI [4]	2012	1 LiDAR, 4 video cameras	151 / Low	48791 / 10	10 / 64 / 2 / 120	Diverse scenarios (urban, rural), various objects	3D bounding boxes, 8 classes
KAIST [3]	2017	3 LiDAR, 2 stereo cameras, 1 RGBT camera	24 / Medium	17940 / 20	10/32/2/70	Different times of day, different drivable environments	Bounding boxes, 6 classes
A3D [10]	2019	1 LiDAR, 2 video cameras	— / Medium-High	— (39179 LiDAR) / 55	10 / 64 / 2 / 120	Different scenarios, times of day and weather, high density of objects	3D object annotations, 7 classes
Argoverse [2]	2019	2 LiDAR, 7 video cameras, 2 stereo cameras,	113 / Medium	<i>— /</i> 30	10 / 32 / — / 200	Real world scenarios, different weather conditions and times of day	3D bounding boxes, 15 classes
Astyx Dataset HiRes2019 [8]	2019	1 LiDAR, 1 radar, 1 video camera	_/	546 / 30	13 / 16 / 3 / 100	3D object detection, sensor fusion	3D objects (7 classes)
H3D [9]	2019	1 LiDAR, 3 video cameras	160 / Medium	27721/30	10 / 64 / 2 / 100	Urban driving situations	3D bounding boxes, 8 classes
Lyft Level 5 [7]	2019	5 LiDAR, 6 video cameras	350 / Medium	_/_	10 / 64 / — / —	Visual driving scenes, restricted geographic area	Semantic

Table 1 – LiDAR datasets for autonomous	driving. (—) indicates that no information	is provided. (Continued from previous page)

DATASET NAME	YEAR	TYPE OF DATA	NUMBER OF SCENES / VARIABILITY	VIDEO FEATURES (NUMBER OF FRAMES / FRAME RATE (fps))	LiDAR FEATURES (FRAME RATE (Hz) / NUMBER OF BEAMS / ACCURACY (cm) / RANGE (m))	FEATURES	ANNOTATIONS
nuScenes [1]	2019	1 LiDAR, 5 radars, 6 video cameras	1000 / Medium	1.4M / 12	20 / 32 / 2 / 70	Urban scenes, different weather and lighting conditions	Semantic (23 classes, 8 attributes) and 3D bounding boxes
Waymo Open Dataset [12]	2019	LiDAR, video cameras	1950 / Medium-High	230000 / 10	10/—/—/75	Different times and lighting conditions	3D bounding boxes (LiDAR), 2D bounding boxes (video)
A2D2 [5]	2020	5 LiDAR, 6 video cameras	— / Medium-High	41277 (12497 LiDAR) / 30	10 / 16 / 3 / 100	Commercially usable dataset. Different scenarios (urban, motor-ways and country roads)	Semantic segmentations (38 categories), 3D bounding boxes (14 classes)
ApolloScape Original [6]	2020	LiDAR, radar, video	— / Low	12720/2	10 / 64 / 2 / 120	Urban driving situations, different weather and lighting conditions	Based on LiDAR data (5 classes)
CADC [11]	2020	1 LiDAR, 8 video cameras	75 / Medium	56000 / 10	10 / 32 / 3 / 200	Adverse weather conditions	10 classes, 3D bounding boxes
PandaSet [13]	2020	2 LiDAR, 6 video cameras	100 / Medium	48000 / 10	10 / 64 / — / 200	Different environments and lighting conditions	28 classes, 37 semantic labels

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
0	L.s.	No	Number	No light source	No light available	Sensor will re- ceive no light, but thermal noise or black current can cause wrong in- put	Highly underexposed image where black-level noise makes up most of the data. Integration test: system is self-aware that its output (or output at these areas) are not trustworthy	Filters designed to remove sig- nals from other emitters (other LiDAR sensors in the scene) end up removing own emitter signal.
e0	Emitter	No	Number	No light source	No light available	Sensor will re- ceive no light, but thermal noise or black current can cause wrong in- put	Highly underexposed image where black-level noise makes up most of the data. Integration test: system is self-aware that its output (or output at these areas) are not trustworthy	The emitter is not working so that no light is emitted into the scene, hence no light is detected and all data is invalid.
6	L. s.	As well as	Number	Mirrors fake additional light sources	L.s. can appear at locations other than where they are	Algorithm con- fuses position of light sources	L.s. as well as mirror image of the same l. s. are visi- ble in the image. Critical ex- ample for stereo vision: L.s. and reflection are on the same epipolar line (e.g. table with candle with a large mirror di- rectly behind it).	Another emitter is part of the scene causing erratic measurements or loss of values.
еб	Emitter	As well as	Number	Mirrors fake additional light sources	L.s. can appear at locations other than where they are	Algorithm con- fuses position of light sources	L.s. as well as mirror image of the same l. s. are visi- ble in the image. Critical ex- ample for stereo vision: L.s. and reflection are on the same epipolar line (e.g. table with candle with a large mirror di- rectly behind it).	Mirror images of emitter are confused to be emitters. result- ing in depth measurements rep- resenting surfaces that do not exist.

Table 2. LiDAR entries. Abbreviations: n.a. is 'Not applicable'; l.s. is 'light source'

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
7	L. s.	As well as	Number	Mirrors fake additional light sources	Increases shadow complexity	Algorithm de- tects more light sources than exist	A light source and its clear reflection are near-perfect aligned on the same epipolar line	Noise-reduction parts interpret emitter signal as background noise \rightarrow signal removed
12	L. s.	Spatial periodic	Number	Several light sources are configured in periodic manner	Consequences depend on com- bined parameters	Hazards depend on combined parameters	There is a periodically or- dered array/line of light source aligned on the same epipolar line for both cameras (this can occur at large dis- tances or when aligned with the horizon-line)	L.s. in a straight line pointing at receiver deliver multiple peaks of background signal (reduced contrast vs. emitter and jump- ing distances)
e12	Emitter	Spatial periodic	Number	Several light sources are configured in periodic manner	Consequences depend on com- bined parameters	Hazards depend on combined parameters	There is a periodically or- dered array/line of light source aligned on the same epipolar line for both cameras (this can occur at large dis- tances or when aligned with the horizon-line)	Due to the sampling nature of LiDAR rays, their spatial grid leads to aliasing effects (alias- ing of emitter signal, not detec- tor sensor).
21	L. s.	Less	Position	L.s. near to re- ciever	Lighting of scene can be too strong	Over- and under- exposure in same scene possible	L.s. visible in image is near to the camera and overexposed while areas surrounding the l. s. quickly get dark and under exposed (e.g. room only lit by a candle)	Area directly next to adjacent light source are saturated and re- turns false readings
e21	Emitter	Less	Position	L.s. near to re- ciever	Lighting of scene can be too strong	Over- and under- exposure in same scene possible	L.s. visible in image is near to the camera and overexposed while areas surrounding the l. s. quickly get dark and under exposed (e.g. room only lit by a candle)	Response from surface near to emitter is very strong, receiver gets saturated \rightarrow sensor has a minimum working distance. Objects nearer to the sensor may be missed or distances are wrong

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
e22	Emitter	Less	Position	L.s. near to re- ciever	Light intensity may decrease (with increasing distance from light source) sig- nificantly within scene	Only parts close to light source sufficiently illuminated	Scene with extreme light fall- off: minority of image is well lit with a rapidly decreasing illumination around it	Unexpected strong fall-off of emitter signal, reduced working distance
26	L. s.	Part of	Position	Part of light source is visible	L.s. at the im- age's edge looks different than in the middle	Overexposure (of image parts)	L.s. in image is cut apart by image border	Partially cut apart light source (e.g. sun) not correctly filtered and interpreted as emitter sig- nal. jumping values at sensor border
e26	Emitter	Part of	Position	Part of light source is visible	L.s. at the im- age's edge looks different than in the middle	Overexposure (of image parts)	L.s. in image is cut apart by image border	Imperfect alignment between emitter volume and receiver vol- ume. only part of emitter signal is received (remainder outside of sensor/mirror sweep area) \rightarrow less signal at edges results in higher noise
45	L. s.	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. can be directly visible from reciever	Overexposure (of image parts) - lo- cal outshining	L.s. is prominently visible in image and is surrounded by considerable overexposed ar- eas	L.s. in view creates bad contrast vs. emitter \rightarrow no distance reading at light source center
45,2	L. s.	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. can be directly visible from reciever	Overexposure (of image parts) - lo- cal outshining	L.s. is prominently visible in image and is surrounded by considerable overexposed ar- eas	Another emitter is part of the scene causing erratic measure- ments or loss of values.
46	L. s.	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. at the im- ages edge looks different than in the middle	Reflections of op- tics in image	Clearly visible Bokeh to- gether with the l. s. causing it (e.g. the sun)	Bokeh effect caused by l.s. in receiver optics creates artificial echos.

 Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
e46	Emitter	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. at the im- ages edge looks different than in the middle	Reflections of op- tics in image	Clearly visible Bokeh to- gether with the l. s. causing it (e.g. the sun)	Bokeh effect caused by emitter signal in receiver optics creates artificial echos.
47	L. s.	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. can be directly visible from reciever	Virtual rays in image	L.s. together with clearly vis- ible streaks of light radiating in a radial fashion from L.s.	L.s. in receiver optics creates a lens flare effect which produces false data.
e47	Emitter	In front of	Position	L.s. is part of scene (in front of reciever)	L.s. can be directly visible from reciever	Virtual rays in image	L.s. together with clearly vis- ible streaks of light radiating in a radial fashion from L.s.	Emitter signal creates a lens flare effectin receiver optics which produces false data.
50	L. s.	Behind	Position	L.s. behind re- ciever	Objects illumi- nated with small angle between direction of light and direction of view	Small irregular- ities on object surfaces with same colours as surroundings may remain undetected	Scene where sun (or other strong light source is directly behind the reciever. Relevant untextured object's structure is not reconstructed due to missing object self-shading.	Second emitter close to system pointing into the same direction is confused with own signal
52	L. s.	Behind	Position	L.s. behind re- ciever	Little contrasts on smooth surfaces	Reflecting areas oriented parallel to image plain may appear over exposed	Sun behind camera is casting light on a white wall causing overexposure	L.s. (non-emitters) behind sen- sor pointing into the same direc- tion is confused with signal
63	L. s.	Faster	Position	L.s. moves faster than expected	L.s. stays shorter at a place than ex- pected	Too weak light	L.s. visible in image with a long elongated thin shape (e.g. neon tube) creating an unusually prolonged overex- posed area	Motion-blur of light source re- sults in a noise background which is elongated and paral- lel to existing scan lines. Sig- nal/Noise behavior of neighbor- ing lines are different thus cen- tral line gets confused with sig- nal

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
e63	Emitter	Faster	Position	L.s. moves faster than expected	L.s. stays shorter at a place than ex- pected	Too weak light	L.s. visible in image with a long elongated thin shape (e.g. neon tube) creating an unusually prolonged overex- posed area	Emitter direction movement control is faulty, resulting measurements are faulty
e100	Emitter	Slower	Spectrum	Light of emitter is moving slower than expected	Wrong assump- tions for speed of light	theoretic speed of light is assumed instead of group velocity	n.a.	Echo time measurement trans- lates to faulty distances
102	L. s.	More	Texture	L. s. has too much texture	The l. s. pro- duces a texture of its own by pro- jecting a textured light beam (vir- tual texture)	Texture of emit- ted light is con- fused with texture on object. This creates false pos- itive detections.	L.s. projects a texture onto a surface while a very similar texture is already present next to it as part of another object's surface texture, both textures are aligned on the same epipo- lar lines	L.s. encoding is equiva- lent/similar to emitter signal
e102	Emitter	More	Texture	L. s. has too much texture	The l. s. pro- duces a texture of its own by pro- jecting a textured light beam (vir- tual texture)	Texture of emit- ted light is con- fused with texture on object. This creates false pos- itive detections.	L.s. projects a texture onto a surface while a very similar texture is already present next to it as part of another object's surface texture, both textures are aligned on the same epipo- lar lines	see 449
e107	Emitter	As well as	Texture	L. s. projects combination of two textures, one expected, the other unexpected	Blending of light- ings, complex illumination and shadowing	Small changes in light source configuration may cause large differences in responses of CV algorithm (e.g. Moire)	L.s. projects a thin struc- tured pattern onto a surface that produces two distinctly different Moire patterns in the left/right camera	Detector resolution mismatch- ing with spatial resolution of signal encoder creates aliasing artifacts. windowing confuses neighboring encodings

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
125	L. s.	More	Intensity	L.s. is too strong	Too much light in scene	Overexposure of lit objects	Directly lit object is overex- posed in an otherwise cor- rectly exposed scene/image	Background signal in general much brighter than expected. detector saturated \rightarrow signal is lost
e125	Emitter	More	Intensity	L.s. is too strong	Too much light in scene	Overexposure of lit objects	Directly lit object is overex- posed in an otherwise cor- rectly exposed scene/image	Emitter intensity too strong. Re- sponse is enlarged and over- flowing/bleeding at object edges
e140	Emitter	More	Beam	Large beam angle, even omni-direction emission of light	All objects will be lit	Reflections in all shiny surfaces possible	Very bright scene without overexposure but very little contrast due to approximating an ambient lighting situation with nearly no shadows (self- shading neither)	Spread of energy and incon- clusive/faulty detector measure- ments. Multiple targets are summarized to single targets
e141	Emitter	Less	Beam	Focused beam	Only fractions of objects will be lit	Large parts of scene may be dark	Headlight situation with only a small part of the scene suf- ficiently being lit. Large parts are underexposed.	Emitter fingers have too much gap between them missing cru- cial details. spatial aliasing
142	L. s.	Less	Beam prop- erties	Focused beam	Only fractions of objects will be lit	Unsmooth illumi- nation of surfaces	Scene where a prominent object is only half lit by the scene's light source while a large portion remains severely underexposed	Object partially overexposed by background level. response of remainder correct \rightarrow shape misinterpreted
e142	Emitter	Less	Beam prop- erties	Focused beam	Only fractions of objects will be lit	Unsmooth illumi- nation of surfaces	Scene where a prominent object is only half lit by the scene's light source while a large portion remains severely underexposed	Emitter finger signal on part of object, remaining object unhit → object shape misinterpreted
183	Medium	Less	Transparency	Medium is opti- cally thicker than expected	Less light can pass through	Less contrast than expected could result in mismatches	Fog / haze in image reduces visibility depending on dis- tance from reciever	Emitter light is absorbed by medium \rightarrow number of invalids increases with distance

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
189	Medium	As well as	Transparency	Two different me- dia have a differ- ent optical thick- ness	Refraction oc- curs: changes the path of light from the object to the reciever	The object ap- pears to be displaced	There is a large part of the scenery clearly visible within a different medium than in di- rectly in front of the reciever (e.g. view clean/clear water with lots of details visible be- neath the water surface)	Objects are within unexpected medium \rightarrow refractive index different \rightarrow scene displacement
200	Medium	As well as	Spectrum	Medium has similar colour as nearby light source/object	Low contrast	Objects and medium become indistinguishable	Scenery contains a medium (air, water) with comparable colour and particles/textures as the objects in the scene	Medium filters emitter frequen- cies needed for signal identifica- tion
237	Medium	No	Particles	No particles in the medium	No particles in the medium which scatter transmitting light	If particles are needed to e.g. visualize flow dynamics, this will be hampered	The border between two me- dia is very clean and the medium is clean as well thus preventing the detection of the medium border itself	Medium border/existence is missed because of unexpected clarity. border is not visible (refraction but no reflection)
244	Medium	More	Particles	Particles are large(r than expected)	Particles appear as distinct objects	Particles are mis- interpreted as ob- jects	Large hailstones, snowflakes or raindrops look like parts of the actual scene/objects in the scene thus creating faulty matches	Large particles reported as ob- stacles
245	Medium	More	Particles	Particle size is bigger than the light's wave- length	Geometric Scat- tering	See Less Trans or More Texture	Cloud of visible particles (e.g. pollen, small leaves) in the air are obscuring the scene	Cloud of visible particles (e.g. pollen, small leaves) in the air are obscuring the scene or cre- ate false echos in the air
259	Medium	Where else	Particles	Particles fill up different parts of the scene with different density	Different areas of scene exhibit dif- ferent visual ef- fects	Different recog- nition quality throughout an image	Scene is split into two roughly equally big parts: one with- out particles and another with considerable amount of par- ticles (e.g. a view with a roof covering a area where no snow/rain is falling and an outside part full of rain/snow)	Scene is split into two roughly equally big parts: one with- out particles and another with considerable amount of parti- cles (e.g. a view with a roof cov- ering a area where no snow/rain is falling and an outside part full of rain/snow)

Table 2 – LiDAR entries (*Continued from previous page*)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
266	Medium	Close	Particles	Particles very close to reciever	Single particles may cover larger scene fractions	Single particles are confused with real scene objects	A single particle that is close to the reciever looks very sim- ilar to an object in the scene while both are aligned on the same epipolar lines	Single large particle on sensor screen interpreted as near object (e.g. rain drop/snow flake on sensor window)
271	Medium	Faster	Particles	Particles move faster than ex- pected	Motion blur of particles	Blurred particles obfuscate (parts of) scene	Scene contains particles mov- ing fast enough to have a no- ticeable motion blur	Particles moving with simi- lar speed as the emitter bun- dle cause elongated responses. worst case: response of a non- existent surface.
275	Object	No	Position	Position can- not be defined/ detected	An object's "cen- tral" point cannot be defined	One object is re- ported as several	Large, diffuse or highly struc- tured or flexible objects like clouds, fungus mycelium, or table-cloth is broken into many objects small enough so that noise/speckle filtering might remove them	Broken-up object (fence, bars,) has no clear centroid, noise-removal removes individ- ual speckles thus leaving empty space behind.
294	Object	Close	Position	Object closer to reciever than ex- pected	Object is larger and covers more of the scene than expected	False positive: object not cor- rectly recognized	n.a.	Object is closer than minimum distance of sensor and is missed.
298	Object	Remote	Position	Objectmoreremotefromrecieverthanexpected	Object is smaller than expected	False positive: Object not cor- rectly recognized	n.a.	Object is further away than maximum distance of sensor and is missed.
305	Object	Faster	Position	Object moves faster than ex- pected	Object stays shorter at a place than expected	Transversal mo- tion blur	Object is moving from left to right fast enough to have a no- ticeable motion blur	Objects moving with similar speed as the emitter bundle cause elongated responses. worst case: response of a non-existent surface.

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
316	Object	Less	Size	Object is smaller than expected	Object is too small to be cor- rectly detected by Receiver	No object is re- ported	n.a.	Small target cannot be detected as reflected signal is to weak.
321	Object	Part of	Size	Only Part of Ob- ject area is visible	Object is ei- ther partially occluded	Object is not cor- rectly recognized	Larger parts of an object are occluded (left view vs. right view) so that the remaining parts might get rejected as noise/speckles	Offset between emitter and re- ceiver creates situation were one object is shadowing/hiding an- other object.
326	Object	Part of	Size	One of the Object extents is missing	Degenerated con- figuration of ob- ject surface	CV algorithm fails because of a degenerated case	A large but very thin object is positioned in such a way that exactly one of the two cam- eras sees only the thin edge of it without much surface.	For thin objects, the different position of receiver and emit- ter can cause that the object is simply not measured, because either emitter or receiver light rays miss the objects surface.
341	Object	Faster	Size	Object size changes faster than expected	Object shrinks/increases or pulses re- markably during exposure	Radial motion blur	Scene contains an expand- ing/shrinking object that has a noticeable radial motion blur (not caused by ego-motion!)	Fast changing size of object in- troduces temporal aliasing due to emitter encoding and size change frequency overlaps
365	Object	Faster	Orientation	Orient. changes faster than ex- pected	Object rotates re- markably during exposure	Rotational mo- tion blur	Scene contains a rotating object that possesses noticeable rotational motion blur (not caused by ego-motion!)	If an object rotates around its own axis and has very different reflection properties on different sides, the rotation and the emit- ter movement can cause tempo- ral aliasing effects.
376	Object	Less	Complexity	Object is less complex than expected	Object lacks nat- ural features	Insufficient amount of natural features leads to faulty/no results in 3D reconstruction or self-localisation	Simple non-planar object without texture or self- shading (e.g. grey opaque sphere)	Missing complexity of an object make 3D point and model align- ments difficult, hence tempo- ral aggregation of data is ham- pered.

Table 2 - LiDAR entries	(Continued from	previous page)
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HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
383	Object	Other than	Complexity	Object has a complete differ- ent complexity (shape) than expected	Parts of object are identical	Mismatch of object parts in stereo lead to wrong depth or shape recognition	Locally simple repeating parts of an object that is oth- erwise complex (e.g. house faCCade with a regular grid of windows)	Noise compensation mecha- nisms that assume a certain maximum and minimum fre- quency in the perceived surface get confused, therefore data is interpreted as noise or vice versa.
449	Object	Less	Texture	Object has less texture than ex- pected	Texture is no significant identi- fication property	Texture-based CV algorithm is hampered	Two objects at the same im- age height (on epipolar lines) have very little texture thus al- lowing a mismatch	Encoding of signal is reproduced or counter- acted/"cancelled" by an object's surface (e.g. Helmholtz res- onators, stealth tech.)
459	Object	Spatial aperi- odic	Texture	Object texture is aperiodic	Texture does not precisely repeat, but variations are irrelevant	Irregular (stochastic) mismatches in stereo images	A large area is loosely peri- odically tiled (w.r.t. epipo- lar lines) but the tiling is not perfect (e.g. floor tiling with some variations)	see 449
476	Object	No	Reflectance	Object has no re- flectance	No light reflected	Object confused with shadow	Well-lit scene contains a very dark/black object that appears to have has neither texture nor shading due to its low albedo	Object with very low albedo is not returning signal \rightarrow invisible
478	Object	More	Reflectance	Object has much Reflectance (more than expected)	Shiny surface - mirror	Object not recog- nized	Object has strongly reflecting material that creates an arbi- trary mirror-image as the ob- ject's texture	Mirroring parts of an object cre- ates distorted response. object shape misinterpreted
479	Object	More	Reflectance	Object has much Reflectance (more than expected)	Overexposure of the reciever	Reflected objects taken for real	Object has strongly reflecting material that mirrors larger parts found on the same epipolar line	Object has strongly reflecting surface and is partially flat and therefore the sensor perceives a mirrored and translated version of the reality.

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
482	Object	As well as	Reflectance	Object has both shiny and dull surface	Diffuse re- flection with highlight/glare	Local overexpo- sure due to glares	Object has a large glare spot on its surface that obscures same areas in the left/right im- age	Object has a highly reflective spot on its surface that saturates parts of the receiver introducing "blind spots". This glare effect can apply to neighboring areas of the reflection
489	Object	Where else	Reflectance	There are multi- ple reflections on different parts of the object	Object creates impression of invalid copies on surface	Reflections with highlights/glare	n.a.	Retro-reflector or other material with a glare effect surrounds ob- ject with fake copys/distances
502	Object	More	Transparency	Object is highly transparent	Transparent object	Object not recog- nized	Highly transparent empty object covers large parts of the scene, the scenery behind the object is clearly visible	Highly transparent empty object covers large parts of the scene, distances for scenery behind the object is measured
504	Object	More	Transparency	Object is more transparent than expected	Transparent object	Objects within it not correctly recognized due to distortions, e.g. through glass	Highly transparent object en- compassing a second opaque object that gets distorted due to the transparent object's shape	Highly transparent object en- compassing a second opaque object that gets distorted due to the transparent object's shape
509	Object	As well as	Transparency	Object is both more and less transparency than expected	Object consists of parts with high and low transparency	Object itself and objects behind it are merged	Scene contains a large object with a mixture of high trans- parency and low transparency. The object and the scenery be- hind it are close to both cam- eras so that occlusions occur	Scene contains a large object with a mixture of high trans- parency and low transparency. The object and the scenery be- hind it are close to both cameras so that occlusions occur
536	Objects	No	Number	No objects	Scene with no ob- jects (only light sources and me- dia)	Non-existing objects might erroneously be reported by CV algorithm	Scene without visible objects of any kind. only homoge- neous medium and pixel noise is visible	Perceived scene is empty (also no ground floor) \rightarrow noise falsely interpreted as response

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
539	Objects	More	Number	More objects than expected	Scene is more complex than expected	False negatives: objects are missed	Scenery made up of many in- dividually different objects at different distances that clutter the scene and create a highly variating disparity range	Scenery made up of many indi- vidually different objects at dif- ferent distances that clutter the scene and create a highly variat- ing surface.
542	Objects	More	Number	More objects. than expected	Scene is more complex than expected	An object is cov- ered such that un- covered parts are interpreted as be- longing to differ- ent objects	Two objects occlude differ- ent parts of two other ob- jects. The occluded parts are the exact/near copies of the vice-versa occluded part \rightarrow the first object occludes some- thing that the second occluder reveals (and vice-versa)	Occlusion covers important de- tails of an occluded object which results in a misclassifica- tion/confusion
555	Objects	Spatial periodic	Number	Object arrange- ment is periodical	Reciever resolu- tion and window- ing have to be ap- propriate to cap- ture a characteris- tic arrangement	If resolution of field of view are not appropriate detection based on characteristic arrangements is corrupted	Highly periodic placement of identical objects along the epipolar line creates repeating structures which lead to po- tential mismatches	Periodic structures/placement of objects results in many potential solutions for global registration \rightarrow registration errors
561	Objects	In front of	Number	A number of Ob- jects is in front of each other (in respect to the re- ciever)	They cover each other	They are indistin- guishable	Identical objects are arranged in such a way that one of the objects completely covers the other object in one of the im- ages. Thus the covering ob- ject can create faulty matches with the covered object	Multiple objects are arranged in-line, only the closest object is perceived hence the object count is only one.
586	Objects	Spatial periodic	Positions	Objects are lo- cated regularly (different kind)	Different kind of objects appear in a geometrically regular pattern	Only regularity detected, but not the individual objects	Similar objects (but not iden- tical) are arranged in a highly periodic fashion on the epipo- lar line	See 383

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
594	Objects	Close	Positions	Multiple objects closer together than expected	Visible connec- tion between multiple objects is strengthened	Multi-targets can not be separated, as the distance between them is ; 1/2 pulse length	n.a.	Multiple targets are summarized to single targets
608	Objects	More	Occlusion	More objects oc- clude each other than expected	Less details of objects are visible	Detection quality is decreased by less information of needed Objects	Some objects are positioned at two distinct distances. The frontal objects create consid- erable occlusions that might prevent the correlation of the backside objects	Some objects are positioned at two distinct distances. The frontal objects create consider- able occlusions that might cause the background objects to be confused with noise.
626	Objects	Spatial aperi- odic	Occlusion	Occlusion creates a chaotic /un- ordered pattern	Occlusions are chaotic	CV algorithm is not handling oc- clusions correctly	Scene is dominated by an aperiodically perforated ob- ject near to the reciever thus occluding many parts of the scene behind the object	Occluder is perforated object which is creating only noise at its position \rightarrow only occlude de- tected with high noise level
651	Objects	More	Shadowing	More shadowing than expected	Large parts of scene in shadow	Underexposure: objects in shadow not detected	Large parts of a well lit scene are underexposed due to large shadows cast by objects not seen in the scene.	Additional emitter ("light source") is partially shadowed making its detection/filtering harder
671	Objects	Spatial periodic	Shadowing	Spatial periodic shadows, there is some order/rule as to what parts of an object are shaded	Regular shadows creates a pattern	CV algorithm confuses shadow pattern with object	Highly periodic shadows along epipolar line creates repeating structures which lead to potential mismatches	Interference from another emit- ter ("light source") is periodi- cally shadowed \rightarrow harder to at- tribute to second emitter thus fil- tering hampered

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
687	Objects	More	Reflectance	There are more reflections be- tween objects than expected	Creates multiple views within the scene	CV algorithm might confuse reflectance with reality and infer wrong posi- tion/relation data	Both object and its clear re- flection are visible on the same epipolar line (and same distance) in both left+right image. The mirrored object is symmetric (mirror image looks like the original object) which can lead to a faulty cor- relation.	Reflected objects in path of re- flection are measured instead of the reflecting surface. scenery in reflection not visible in scene otherwise
688	Objects	More	Reflectance	There are more reflections be- tween objects than expected	Can create mul- tiple visible instances of the same object	CV algorithm de- tects more objects than there are in the scene	Both object and its clear re- flection are visible on the same epipolar line (and same distance) only in one of the two images (the other image shows only the object itself). The mirrored object is sym- metric (mirror image looks like the original object) which can lead to a faulty correla- tion.	Reflected objects in path of re- flection are measured instead of the reflecting surface. Reflec- tion shows parts/objects already visible in the point cloud (dupli- cation).
693	Objects	Part of	Reflectance	A reflection on an object is partially visible	A highlight in an object is partially covered by an- other	Overblending - partial hampering of correct situa- tion recognition	A prominent glare spot is only visible in one of the two im- ages	Glare spot (e.g. retroreflec- tor) creates severe overexpo- sure at a surface point \rightarrow other object's geometry surrounding glare spot reduced
694	Objects	Reverse	Reflectance	Reciever sees it- self in a reflec- tion instead of ex- pected object	Own body/ re- ciever itself visi- ble as an object	CV algorithm confuses re- ciever/its own body with other objects	Scene contains a clear reflec- tion of reciever (e.g. cam- era head, measurement vehi- cle) that is epipolar aligned with objects/parts that look like parts of the reciever thus leading to a potential mis- match	Reflected objects in path of reflection are measured instead of the reflecting sur- face. Reflection shows ego vehicle/reciever/sensor itself in scene. might result in 3d "ghosts" of reciever in global registration.

 Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
695	Objects	Reverse	Reflectance	Reflections are reversed	Object reflections appear reversed to expected, e.g. upside down, or laterally inverted	CV algorithm confused	Scene contains a large con- cave mirror that shows an clean upside-down copy of parts of the scenery	Concave mirror near to sensor creates upside down response from behind the sensor
698	Objects	Where else	Reflectance	Reflected Object is Transp.	On objects sur- face, reflected and seen through objects merge	Misinterpretation of reflecting object and its as- sociated images	Objects surface shows a blend/mixture of clear reflectance as well as trans- parently parts behind the image	Mixture of reflected scene and background is detected thus making recognition of the re- flection as such difficult
699	Objects	Spatial periodic	Reflectance	Reflection creates an ordered pat- tern	Ordered re- flectance creates a pattern	CV algorithm confuses re- flectance pattern with object or textures	Highly periodic clear reflec- tion of the same object along epipolar line creates repeating structures which lead to po- tential mismatches	Multipath reflections create ghosts/copies of objects or parts of the scenery.
701	Objects	Spatial aperi- odic	Reflectance	Reflection creates a chaotic /un- ordered pattern	Reflection is chaotic/irregular	$\begin{array}{c c} CV & algorithm \\ confused & by \\ irregular & re- \\ flectance & \rightarrow \\ miss-detections \end{array}$	Large parts of the image show an irregular specular reflec- tion (mirror-like but with lots of distortions. not a diffuse re- flectance)	See 383
707	Objects	Close	Reflectance	Reflected object is closer to re- ciever than ex- pected	Reflections are larger and/or brighter than expected	Overexposure: reflection too bright	A large prominent glare spot is created by a l. s. right next to the reciever (but not directly visible on the images)	Retroreflector in near vicinity of emitter creates large amount of stray light signal which sat- urates/corrupts the whole re- sponse
719	Objects	Behind	Reflectance	Reflected object behind reciever	If also a reflect- ing object in front of reciever, in- finite reflections can occur	CV algorithm confused	Receiver is placed between two large parallel mirror fac- ing each other so that "in- finite" number of reflections occur	Reciever is placed between two large parallel mirror facing each other so that "infinite" number of reflections occur

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
729	Objects	Part of	Transparency	Parts of an ob- ject are transpar- ent and allow a part of another object to be seen	Complex mix- ture of multiple objects visible through projec- tion although the objects are not intertwined	Miss-detection of objects as appearances are changed	Object has transparent parts that show a different ob- ject while other parts remain opaque	Transparent parts of ob- ject is missed. This might confuse detec- tion/segmentation/categorization of point clouds
735	Objects	Spatial periodic	Transparency	Transparency creates an or- dered pattern	Regular trans- parencies in scene	CV algorithm confuses trans- parency pattern with object	Highly periodic placement of windows/holes/clearings along epipolar line creates repeating view of a uniform background which lead to potential mismatches	Aliasing effects due to emitter or receiver spatial sampling pat- tern.
748	Objects	In front of	Transparency	Transparent ob- ject in front of another transpar- ent object	Transparency ef- fects accumulate	Objects not cor- rectly separated	Two transparent objects are positioned behind each other so that the scenery behind the last object is still clearly visi- ble (e.g. looking through two windows in series)	Two transparent objects are adjacent, their border is missed/confused \rightarrow two objects perceived as one
758	Objects	Spatial periodic	Wave	Spatial periodic variation of Wave effects (of some objects)	Interferences oc- cur regularly in scene	Confusion of ob- jects causing in- terference effects	Scene contains pronounced refraction rings (e.g. oil slick)	Thin-film interference effects LiDAR echo resulting in false or duplicate measurements.
790	Recv. Opto.	Close	Number	All recievers are close to each other (short baseline)	Short baseline makes triangula- tion results less accurate since the displacement of corresponding image points is smaller	Camera pose esti- mation fails or is inaccurate	Easy to produce by supplying the same images for left/right	Mechanical mounting of detec- tor or emitter is closer than expected, hence time measure- ments are translated into faulty 3D points.

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
803	Recv. Opto.	More	Field of View	Reciever uses a bigger FOV than expected	Focal length smaller than expected	More distant enti- ties not detected	Scene has a wide FOV (¿135deg)	Angle of receiver or emitter is wider than expected, hence time measurements are trans- lated into faulty 3D points.
883	Recv. Opto.	Part of	Viewing po- sition	VPos is Part of scene (within scene)	Sensor too close to scene - scene partially defocused	Defocused ob- jects not correctly recognized	In a scene with considerable depth of field: slightly near objects visible by both cam- eras are out of focus (near plane)	Sensor has a minimal distance and important aspects/details for the application are lost due to neglecting this minimum
892	Recv. Opto.	Spatial aperi- odic	Viewing po- sition	Reciever position is not constrained (perhaps within a given range)	Additional uncer- tainties due to ar- bitrary position of Reciever	Additional uncer- tainties introduce additional un- certainties for the position estimation of objects	Relative position between cameras slightly changed compared to their initial posi- tions/orientations. Extrinsic calibration is thus slightly off	See 790
898	Recv. Opto.	Remote	Viewing po- sition	VPos is more re- mote from scene than expected	Object distance is bigger than ex- pected (out of fo- cus)	Relevant scene details not recog- nized	In a scene with considerable depth of field: slightly dis- tant objects visible by both cameras are out of focus (far plane)	In a scene with considerable depth of field: distant objects cannot be perceived because emitter power does not suffice
899	Recv. Opto.	Remote	Viewing po- sition	VPos is more re- mote from scene than expected	Object have less details than ex- pected	Objects distances estimated less ac- curate	Scenery is in focus but all parts are far away (only small disparities)	Sensors accuracy at high dis- tance is below the threshold to identify important details
904	Recv. Opto.	Faster	Viewing po- sition	Reciever moves faster than ex- pected	Motion blur more likely with longer exposures	Blurred objects miss-detected	Image has parts with clearly visible motion blur	Scanning speed of swipe pattern is too slow to actually capture a fast object.
916	Recv. Opto.	Part of	Transparency	Part of optics are less transparent than expected (e.g. dirt on lens)	Defocused areas	Misinterpretation due to thick dust irregularly dis- tributed on lens surfaces	One camera lenses contain dust/dried mud that creates a partially defocused area in the image	Dust/ dried mud on sensor win- dow prevents measurements in those areas

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
918	Recv. Opto.	Part of	Transparency	Reciever block part of the image	Parts of the image are black	(Partially) Blocked Ob- jects are not detected	Lens body/lens hood is pro- longed and its corners are thus blocking the view	Parts of LiDAR body/mounting protrude into scanning area oc- cluding the scene
921	Recv. Opto.	Other than	Transparency	The transparency of sensor optics is completely dif- ferent from ex- pected, e.g. due to broken lenses	The scene looks completely dif- ferently than expected, e.g. parts of it are multiplied	Strong confusion of CV algorithm if fault not de- tected	Lens is broken cleanly through parts of the center region, apart form the crack the remaining image is clear and sharp	Focus lens of receiver has a crack, light passing through is distorted leading to wrong distance measurements in a straight line
922	Recv. Opto.	Where else	Transparency	Lens body is not completely light proof, light can reach sensor from the side of the body	Flare effects	Overexposure of parts of the scene	Image has pronounces flare effect visible without the em- anating l. s. associated with it	Lens flare effect (see 47) with- out the light source visible in the scene
933	Recv. Opto.	Before	Transparency	Shutter opens or closes before this is expected	Photoelectric events are ex- posed to light out of schedule	Rolling Shutter is causing artifacts which are misin- terpreted as ob- ject properties	Images contain rolling shut- ter artifacts (both cameras are triggered at the same time but moving objects get distorted due to the rolling shutter)	The ray swipe pattern and its temporal correlation with space cause a distorted view of a mov- ing object.
955	Recv. Opto.	Where else	Spectrum	Different parts of spectrum are transmitted to different loca- tions (chromatic aberration)	Washed- out/Defocused edges	Stereo imaging: matching precise- ness decreased	Scene with considerable chro- matic aberration and many visible edges	L.s. spectrum bent in lenses into emitter signal spectrum due to chromatic aberration
961	Recv. Opto.	More	Lenses num- ber	More lenses are in lens assembly than expected	More reflections between lenses	Lens reflec- tions are miss- interpreted as textures or objects	Lens creates double images of parts from the scenery	Intra-lens reflection creates shifted ghost copy of scene

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
982	Recv. Opto.	More	Lenses geometry	More optical effects due to strongly curved lens surfaces	Distortion: barrel or pincushion	Distortion: scene geometry misin- terpreted	Image with radial distortion not perfectly removed (e.g. somewhat bad intrinsic cali- bration)	Receiver has uncorrected lens distortion, point cloud is dis- torted
983	Recv. Opto.	More	Lenses geometry	More optical effects due to strongly curved lens surfaces	Vignetting: im- age darkening to- ward the edges	Vignetting: in- creased	Images have considerably amounts of vignetting and scene contains many objects close to the reciever	Vignetting at receiver leads to reduced working distance at an- gles covered by sensor borders
989	Recv. Opto.	Less	Lenses geometry	Less optical corrections due to weakly curved lens surfaces	Focus range is limited in distance (long- sighted)	Close objects de- focused - poorly recognized	Scene contains some sharp parts in the background and increasingly out-of-focus parts in the foreground	Receiver looses focus at close distances \rightarrow minimal distance and distance errors progressively higher for closer objects
998	Recv. Opto.	Spatial aperi- odic	Lenses geom.	Spatial aper. disturbance or imperfections of lens geometry	Bright rays vir- tually emanate from bright objects within scene	Objects in defect zones of image are not detected correctly	Scratches or rain drops in front of the lens create long bright streaks emanating from all light sources in the scene (lens flare)	Scratches or rain drops on glass window create long bright streaks hence receiver or emit- ter ray positions are wrongly assigned to temporal measure- ments.
1016	Recv. Opto.	Less	Focusing	DoF is smaller than expected	Essential scene parts are out of focus	Blurred image areas misin- terpreted as being empty or "medium only"	Images background and main objects in the scene are out of focus	Receiver out of focus leading to a loss of signal which gets rec- ognized as an empty scene
1059	Recv. Opto.	Where else	Aperture	Aperture form is projected into different places within the image	Chromatic aber- ration in shape of aperture (See More Colour)	Aperture projec- tion is mistaken for an object	Bokeh is visible on the im- age and has a shape and po- sition to make it prone to con- fusions with other parts of the image. Critical case for stereo vision: Bokeh and confusion object lie on the same epipo- lar line	Emitter return signal creates Bokeh effect in receiver optics which mimics additional valid return signals thus creating fake 3D data.

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
1090	Recv. Opto.	No	Optical Point Spread Function	No optical blur- ring before dis- cretisation	Staircasing of edges and lines, Aliasing artifacts	Apparent texture differs from true texture	Image contains strong alias- ing artifacts	Aliasing for distances creates fake steps/edges
1091	Recv. Opto.	No	Opt. PSF	No optical blur- ring before dis- cretisation	Moire patterns in intensity and colour of repetitive textures	Unpredictable differences be- tween appearance of corresponding points/regions	Very different textures in left and right image due to large scale Moire effects	Dominant reflection determina- tion is hampered by additional modulation, temporal measure- ment is faulty.
1094	Recv. Opto.	More	Opt. PSF	PSF's extent is larger than expected	Loss of contrast, PSF effects a bigger neigh- bourhood of pixels	Loss of small objects	One of the two sensors is somewhat out of focus	see 989
1105	Recv. Opto.	Spatial periodic	Opt. PSF	Periodic pattern visible in the PSF, i.e. The PSF is spatially periodic	Additional small scale blurriness creating a spatial pattern	Contoursofobjects are dupli-cated and createpossibilityforconfusions	Inter-lens reflections create visible copy of objects in the image	Reflection on inner surface of sensor window registered as dis- tance (directly in front of sen- sor)
1120	Recv. Electr.	More	Exp./Shutter	Longer expo- sure time than expected	More light cap- tured per image than expected	Overexposure	One of the two images is largely overexposed while the other still shows a lot of detail	Saturation effects in receiver unit lead to partial data loss.
1123	Recv. Electr.	Less	Exp./Shutter	Shorter expo- sure time than expected	Less light cap- tured per image than expected	Underexposure	Large image area is under- exposed and shows a lot of black-level noise there	Little contrast for emitter signal \rightarrow high noise level
1126	Recv. Electr.	As well as	Exposure and shutter	Multiple expo- sures	Multiple frames superimposed into one image	Movement is miscalculated	Two previous frames are blended/combined into one image	Two emitter results are regis- tered as one. the previous emit- ter pulse is attributed to the cur- rent scan \rightarrow ghost distance near to system

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
1162	Recv. Electr.	Part of	Resolution (spatial)	Only along one dimension Resol. is different from expected	Only along one dimension reso- lution is different from expected	Image/pixel ratio other than ex- pected leading to image distortions	Image before rectification originates from considerably rectangular pixels (instead of square, near to e.g. 2:1 ratio)	Mirror has unexpected bent/tilt resulting in an elon- gated/twisted point cloud
1166	Recv. Electr.	Part of	Resolution (spatial)	Part of pixel area is insensitive	Part of pixel area is insensitive	Noise increased	Images contain strong static image noise for well-lit scenes	Receiver activation contain strong static image noise for well-lit scenes
1168	Recv. Electr.	Reverse	Resolution (spatial)	Resolution is n*m instead of m*n	Resolution is n*m instead of m*n	Size of pixel lines and columns reversed, but number of pixels per image as expected	Image has a considerably larger height than width (un- typical image dimensions)	Confusion of azimuth and alti- tude. Point cloud rotated around z-axis by 90deg
1222	Recv. Electr.	Less	Quality	More overflow effects than expected	E.g. blooming	Blooming effects misinterpreted as objects or object parts	Large difference in light in- tensity between indoor and outdoor creates large bloom- ing effects around the edges of a window	Blooming effect at edges may reduce contrast for emitter sig- nal \rightarrow edge is not reconstructed correctly or ghost edges at those positions
1261	Recv. Electr.	Reverse	Quantization / Sampling	Received Inten- sity is encoded inverse to ex- pected	Image is encoded as its "negative"	Scene recog- nition breaks down	One camera delivers image negative instead	Sign for reported distance in- verted or whole scene mirrored at origin
1265	Recv. Electr.	Other than	Quantization / Sampling	Value Quantisa- tion is other than expected	Intensity output is other than expected	Colours and shadows misin- terpreted, derived scene geometry has systematic deviations	Images use logarithmic quantization instead of linear (wrong gamma mapping. mid-tones are washed out)	Distance quantization uses log- arithmic scales, linear was ex- pected

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
3000	Recv. Electr.	No	Local Reg.	There is no lo- cal registration of beam sweeps.	Azimuth/Elevation information is missing; data points represent only 1D distance measurements	Point data is flawed with 3D data squashed into a single line.	n.a.	Point cloud data is misinter- preted.
3001	Recv. Electr.	More	Local Reg.	More degrees of freedom in emit- ter beam than ex- pected.	Sensor data has more dimensions than expected	Assumptions regarding data distribution are wrong.	n.a.	Scene reconstruction results in skewed/squashed point clouds.
3002	Recv. Electr.	Less	Local Reg.	Less degrees of freedom in emit- ter beam than ex- pected.	Sensor data has less dimensions than expected	Assumptions regarding data distribution are wrong.	n.a.	Scene reconstruction results in very sparse representations or skewed geometries.
3003	Recv. Electr.	Less	Local Reg.	Accuracy of axis stabil- ity/calibration is smaller than expected (e.g. eccentricity).	Sensor data has higher inaccu- racy/noise in one dimensions than expected	Assumptions regarding data distribution are wrong.	n.a.	Point cloud data is skewed/bent.
3004	Recv. Electr.	Reverse	Local Reg.	Laser beam rotat- ing in reversed di- rection.	Distance data is registrated for clockwise rotation instead of counter- clockwise (or vice-versa).	Data is flipped for one axis.	n.a.	Invalid interpretation of upside- down scenery.
3005	Recv. Electr.	Other than	Local Reg.	Axis of are non- orthogonally.	Sensor data has higher in- accuracy/noise in certain ar- eas/angles.	Assumptions regarding data distribution are wrong.	n.a.	Point cloud data is skewed/bent.

Table 2 – LiDAR entries (Continued from previous page)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
3006	Recv. Electr.	Where Else	Local Reg.	Twoaxisareswapped(az-imuthwithelevation)	Distance data is registered with swaped axis.	Distance data is transposed.	n.a.	Invalid interpretation of transposed scenery.
3007	Recv. Electr.	Spatial periodic	Local Reg.	One of the axis are highly discretized.	Large gaps be- tween adjecent laser sweeps	Large gaps in consolidated data	n.a.	Gaps in point cloud leading to missed detections.
3008	Recv. Electr.	Spatial aperi- odic	Local Reg.	Several individ- ual measurments in one axis fail (e.g. one of the discrete laser fingers is intermittently failing).	Random gaps between adjecent laser sweeps	Random large- scale gaps consolidated data.	n.a.	Consistent gaps in point cloud (e.g. certain angle/height above ground) may lead to blind spots in the data.
3009	Recv. Electr.	After	Local Reg.	Local registra- tion calibration changes over time (e.g. due to age, tempera- ture).	Consolidated data has mis- alignment based on application runtime.	Data gets more skewed as time passes	n.a.	Skewed data where objects gradually get misinterpreted. Initial calibration gradually ineffective.
3010	Recv. Electr.	Slower	Local Reg.	Local registra- tion assumes slower speeds in scene/objects than actually present.	Temporal ar- tifacts in data consolidation for anything moving in relation to the sensor	Aggregated data contains warped trails of points for moving objects (e.g. flat- tened corkscrew pattern)	n.a.	Temporally skewed data is mis- interpreted.
3011	Recv. Electr.	As well as	Global Reg.	Multiple point clouds are ag- gregated without removing dubli- cate points.	Dublicate data points are cre- ated.	Inaccuracies create multiple copies of ob- jects/scenery in the consolidated point cloud.	n.a.	Shadows and ghost copies of objects create misleading scenery.

Table 2 – LiDAR entries (*Continued from previous page*)

HID	Location	GW	Parameter	Meaning	Consequence	Hazard	Stereo Entries	LiDAR Entries
3012	Recv. Electr.	Other than	Global Reg.	Unexpected global frame of reference.	Assumptions about absolute scale or positions are wrong.	Internal/historic representations are based on a different global frame (e.g. WGS84 vs. UTM coordinates).	n.a.	Planning based on wrong global frame gets confused.
3013	Recv. Electr.	Where else	Global Reg.	Extrinsisc cali- bration (mount- ing position) for sensor is faulty.	Data correct for sensor ref- erence frame is corrupted by bad extrin- sic calibration adding a fixed offset/rotation error.	Consolidated point cloud data has added offset/rotation error	n.a.	Unaccounted offset/rotation creates problems for control loops.
3014	Recv. Electr.	Slower	Global Reg.	Trajectory esti- mation motion understimates movement speed.	GNSS errors and filter errors create faulty positioning estimations.	Consolidated point cloud data has con- stantly changing offsets/rotations.	n.a.	Inaccurate point cloud with faulty data creates problems for navigation/planning.
3015	Recv. Electr.	Temporal aperi- odic	Global Reg.	Extrinsisc cali- bration for sensor is unstable and changes over time.	Data correct for sensor reference frame is cor- rupted by drifting extrinsic cali- bration adding a changing offset/rotation error.	Consolidated point cloud data has added offset/rotation error	n.a.	Unaccounted changing off- set/rotation creates problems for control loops.

Table 2 – LiDAR entries (*Continued from previous page*)

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