Range cameras II

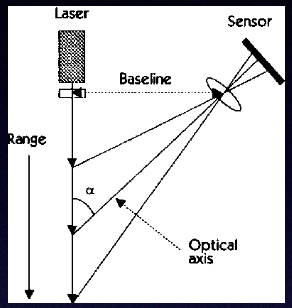
ToF cameras, Lidar, and point-set registration

Per-Erik Forssén
Division of Computer Vision
Department of Electrical Engineering
Linköping University

LINKÖPING UNIVERSITY

Common 3D Cameras

- **Sheet-of-light laser triangulation**
  e.g. SICK, previous lecture.



- **Structured light**
  e.g. Kinect v1, 2010, Apple Face ID sensor 2017, previous lecture.

- **Fringe pattern cameras**
  e.g. Micro Epsilon, next lecture.

- **Time-of-flight cameras**
  e.g. Kinect v2, 2013. VisionPro, Hololens, Azure Kinect, Today.

- **LIDAR sensors**
  Velodyne, Ouster. Work well outdoors. Today.

Common 3D Cameras

- Tekniska museet, Stockholm autumn 2021. Kinect v1. Introduced Nov 2010

The time-of-flight principle

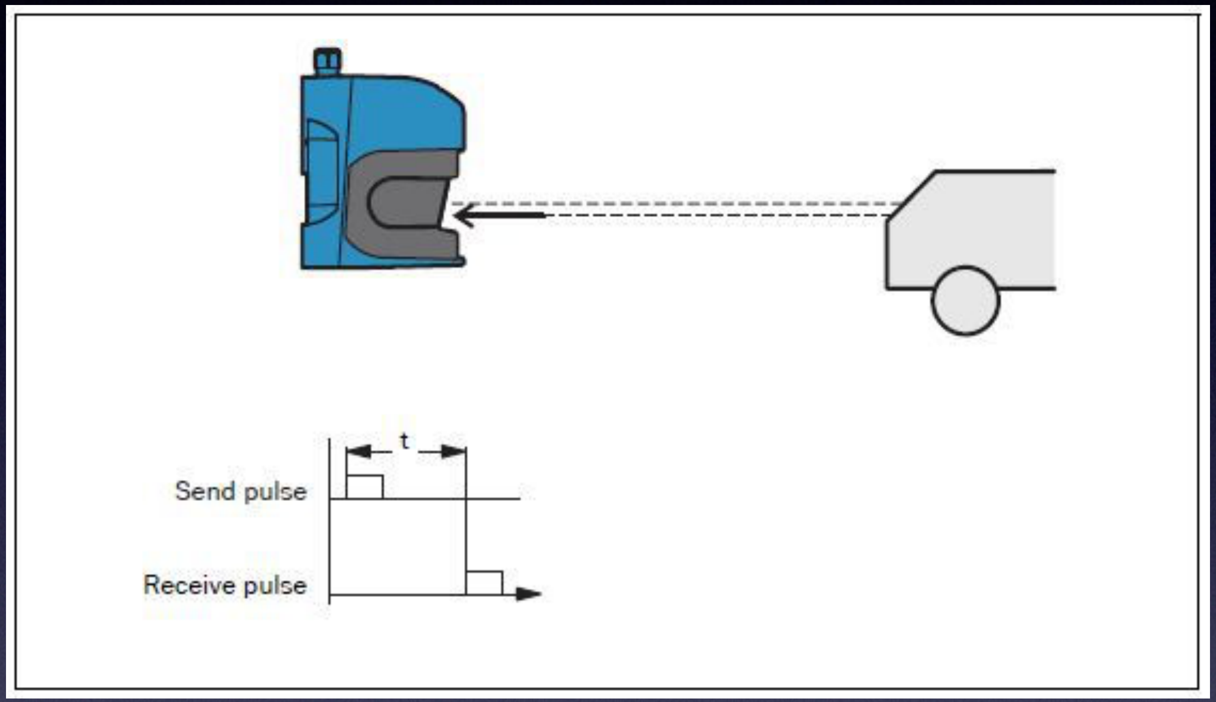
- Classic way to measure depth, used in e.g. RADAR.
- Emit electromagnetic radiation and measure delay until echo is received.
- distance = time*speed-of-light/2

From Wikimedia Commons, the free media repository

The time-of-flight principle

- LIDAR
  (light detection and ranging)
  Same idea as RADAR:

  Emit a pulse and count the time until it returns (i.e. time-of-flight).



Source: SICK

- Measurement relation:

  distance = time*speed-of-light/2

The time-of-flight principle

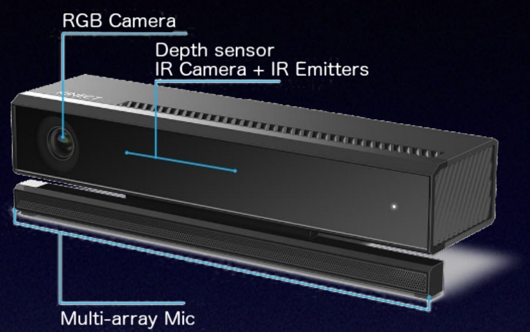
- Requires an extremely accurate clock as $v=3*10^8$ m/s.

clock accuracy	depth accuracy
1 millisecond	±150km
1 nanosecond (10^{-9})	±1.5dm
1 picosecond (10^{-12})	±0.15mm

- Techniques like **continuous-wave**, and **pulsed** time-of-flight maintain high depth accuracy with a less accurate clock.

Time-of-flight cameras

- Continuous wave (CW-ToF)
  +Reduced requirements on clock



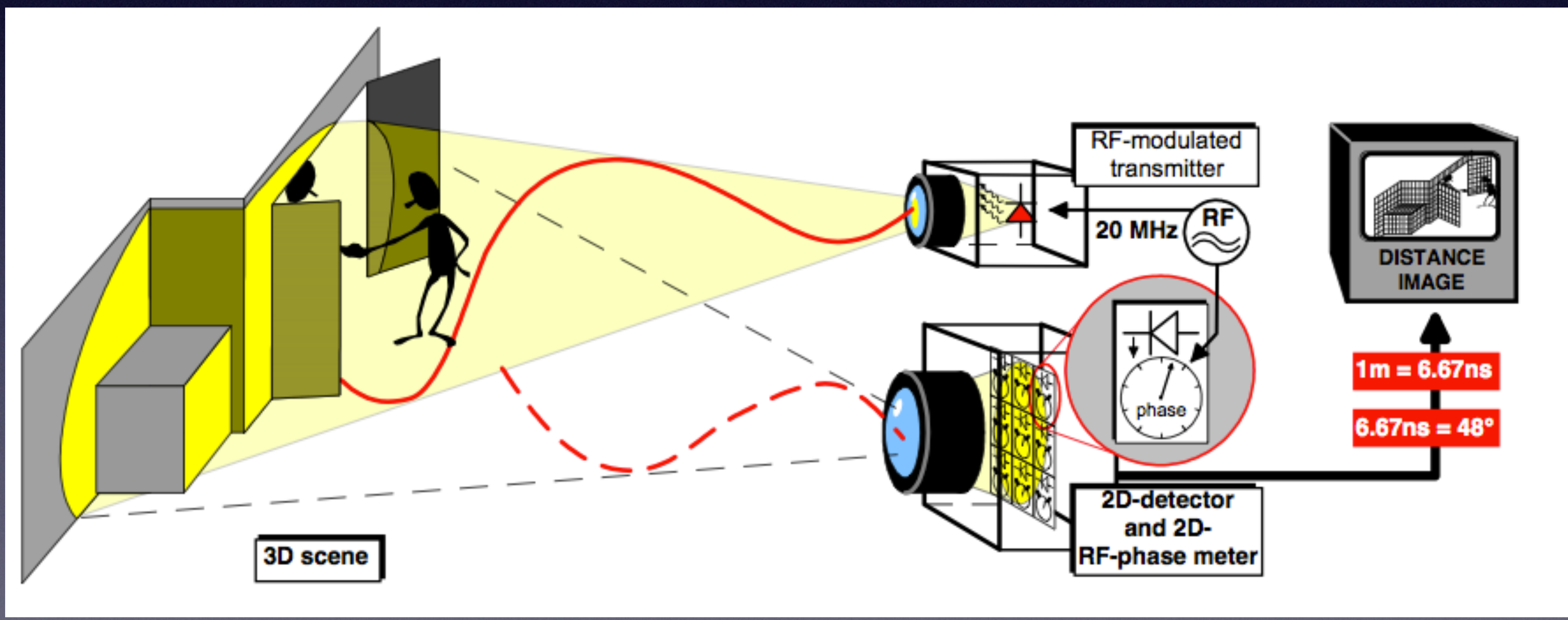
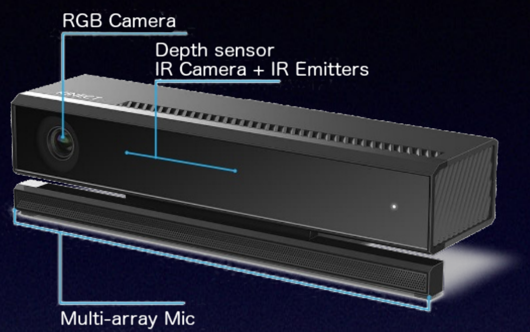


Image: R. Lange PhD thesis, 2000

Time-of-flight cameras

- ToF decoding for continuous wave (CW-ToF)

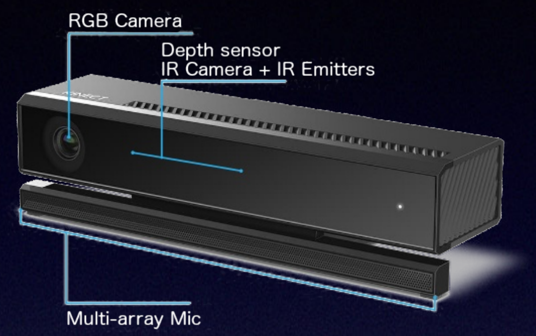


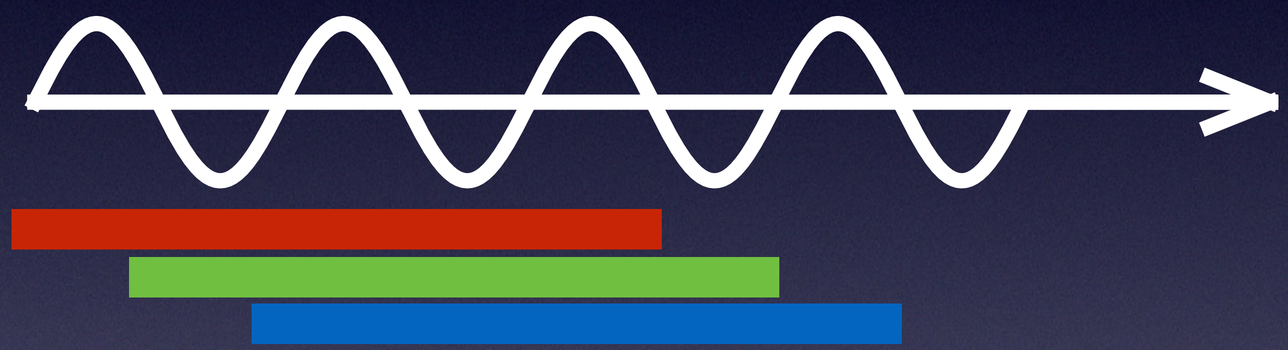
Kinect v2 example

- Emitted signal is amplitude modulated (not frequency modulated)
$$e(t) = I_0(1 + \cos(2\pi f_m t))$$
- Received signal will be
$$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$$
- A correlation is computed in each pixel with three reference signals, to extract ϕ, the phase shift.

Time-of-flight cameras

- ToF decoding for continuous wave (CW-ToF)



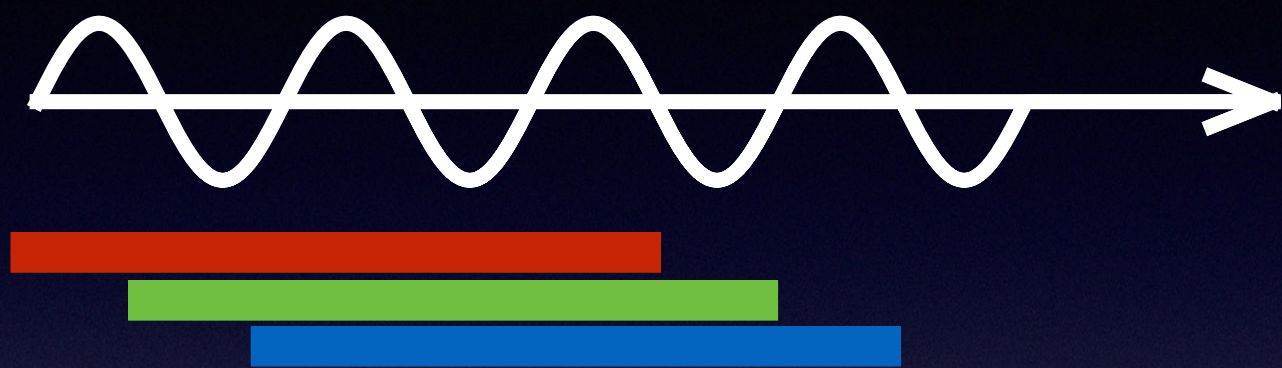


$$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$$

- Create three time-shifted versions of the input

$$s_0(t) = I_0(1 + \cos(2\pi f_m t + 0^\circ))$$
$$s_1(t) = I_0(1 + \cos(2\pi f_m t + 120^\circ))$$
$$s_2(t) = I_0(1 + \cos(2\pi f_m t + 240^\circ))$$

Time-of-flight cameras

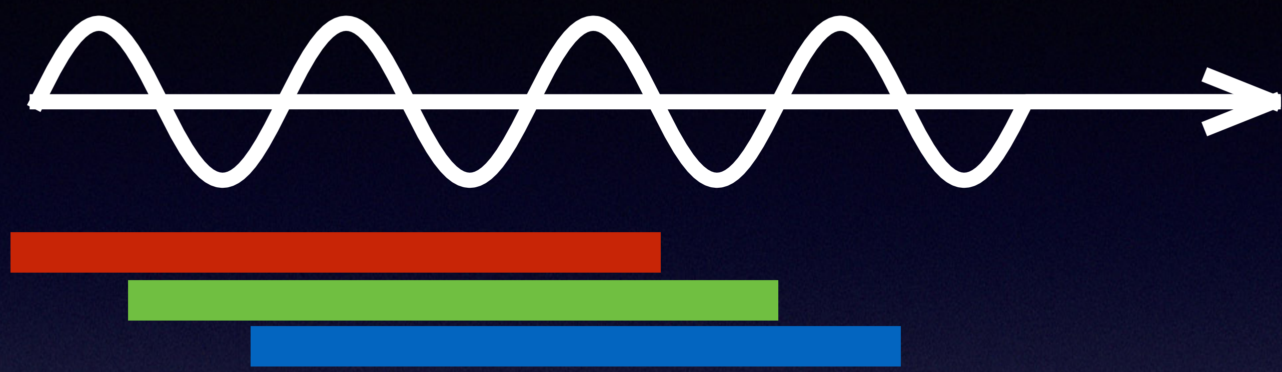


$$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$$

- The sensor correlates the received signal $r(t)$ with the three $s_k(t)$ (integration time t_1-t_0≈5ms)

$$v_k = \int_{t_0}^{t_1} s_k(t) r(t) dt$$

Time-of-flight cameras



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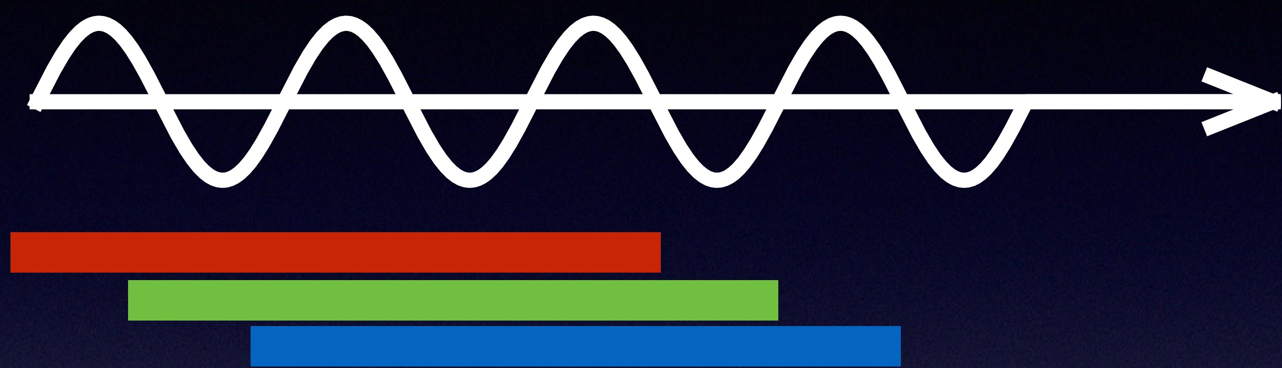
- From v_0, v_1 and v_2 we can now accurately estimate the phase shift

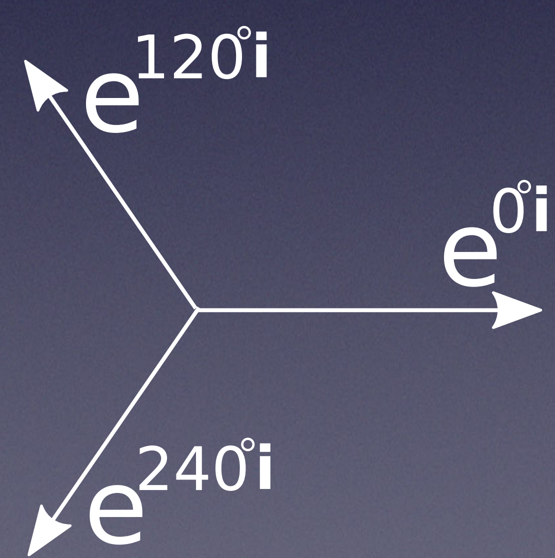
Time-of-flight cameras



$$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$$

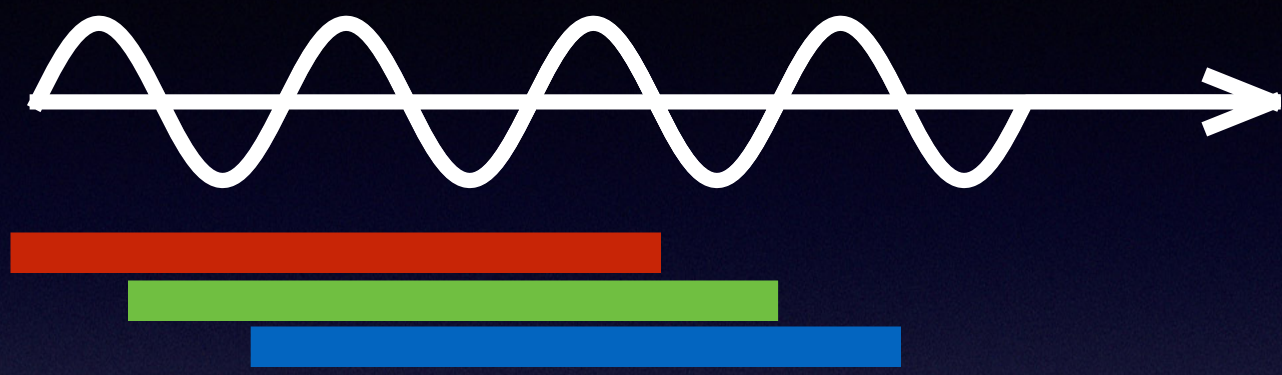
- This is done using a vector summation of the correlations:

$$\mathbf{z} = \sum_{k=0}^{2} v_k e^{-120^\circ \cdot \mathbf{i} k}$$



For a derivation of this expression, see:
Frank et al. Theoretical and experimental error analysis of continuous-wave time-of-flight range cameras , **OE 2009**

Time-of-flight cameras



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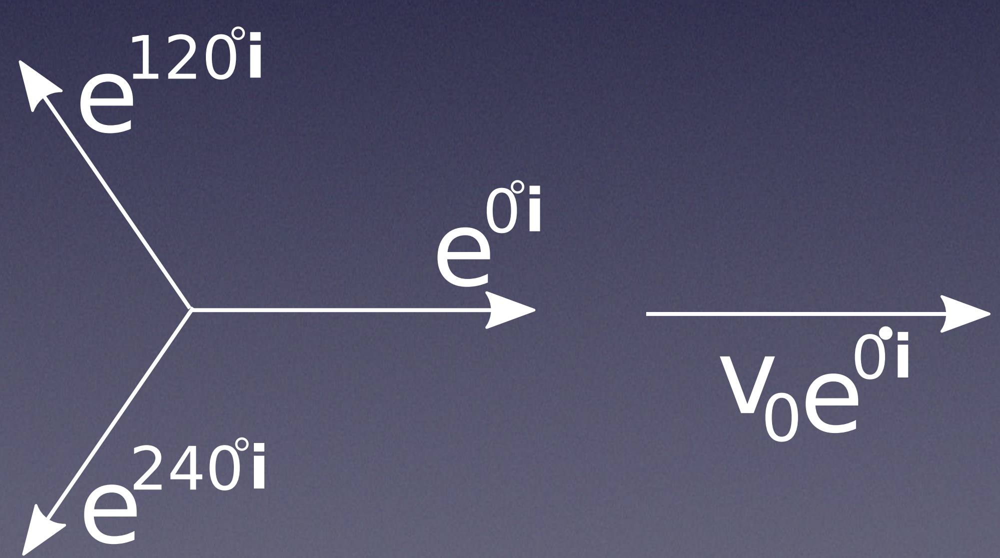
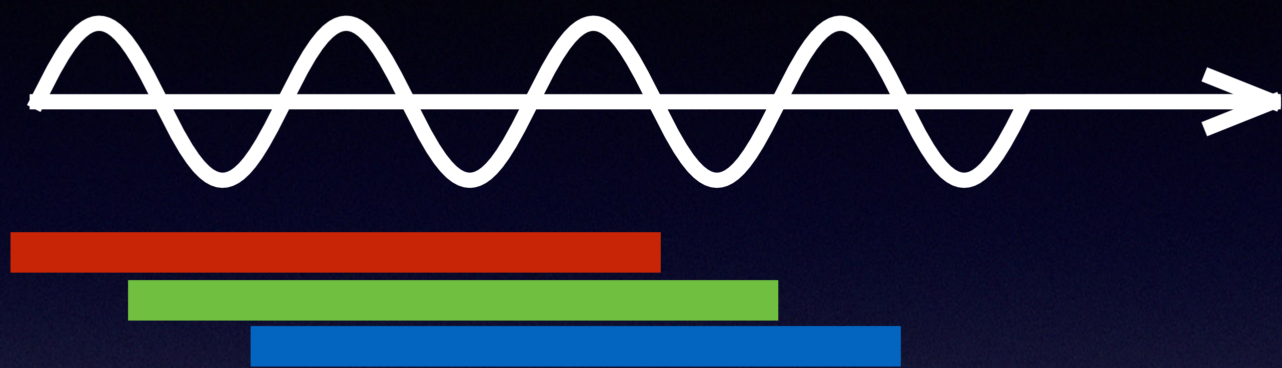


Time-of-flight cameras



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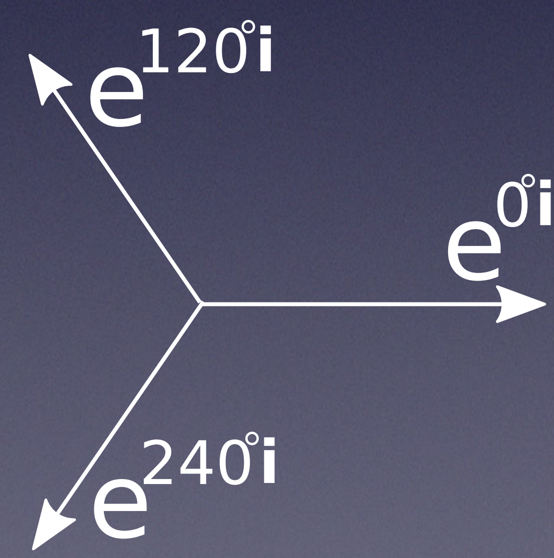
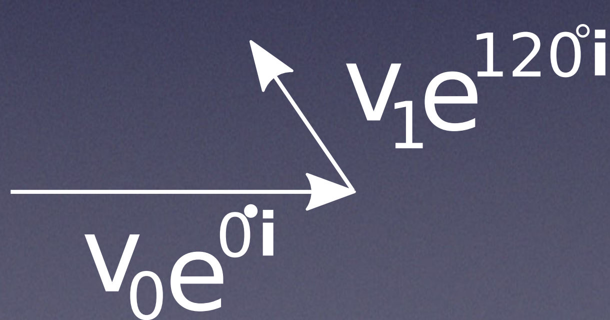
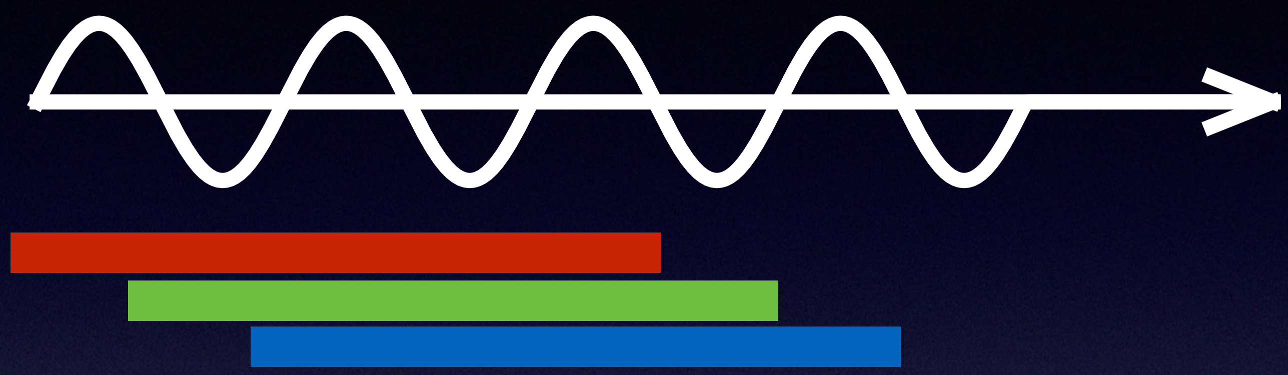




Time-of-flight cameras



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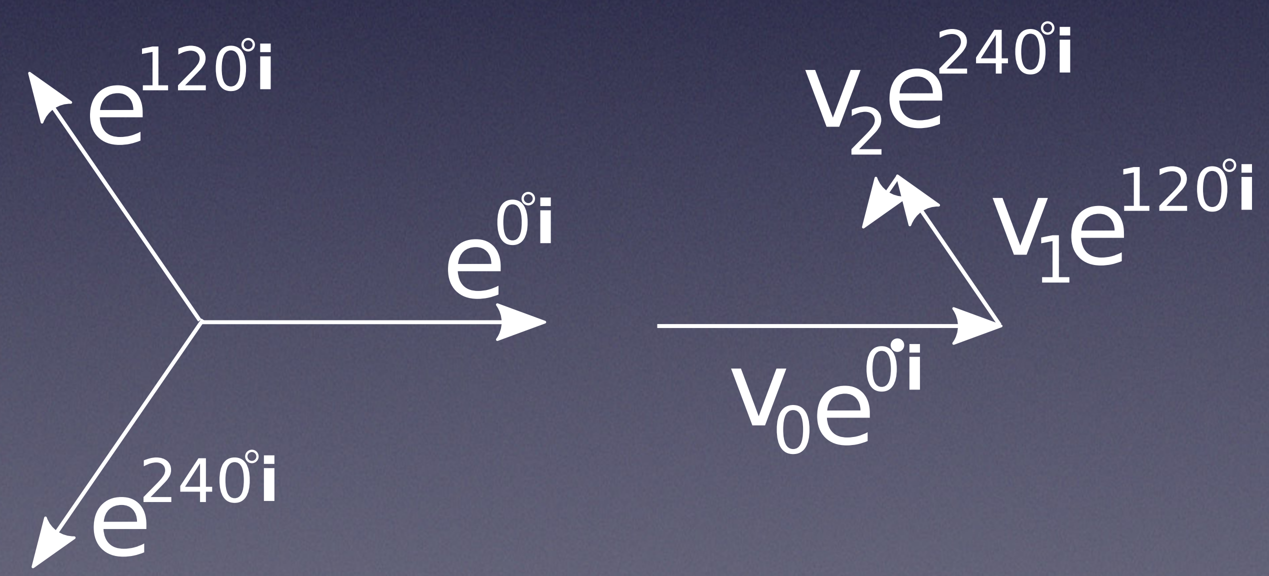
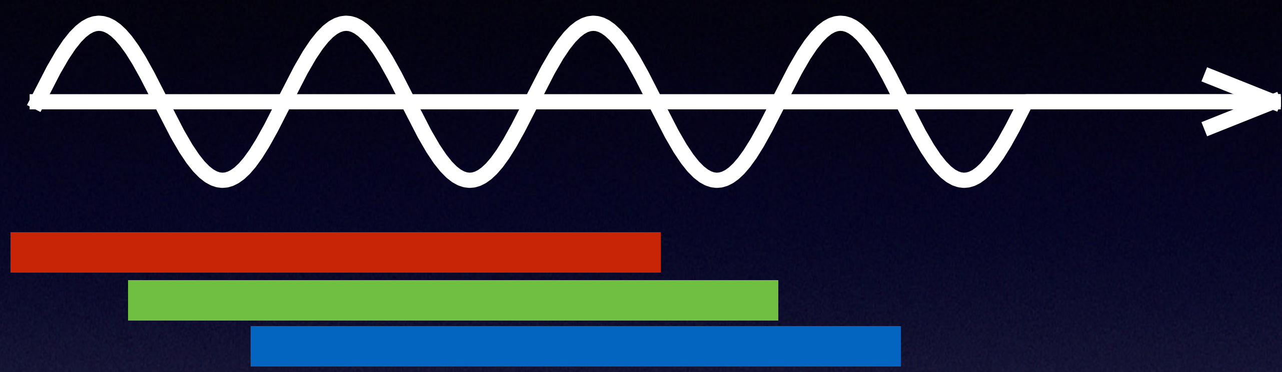


Time-of-flight cameras



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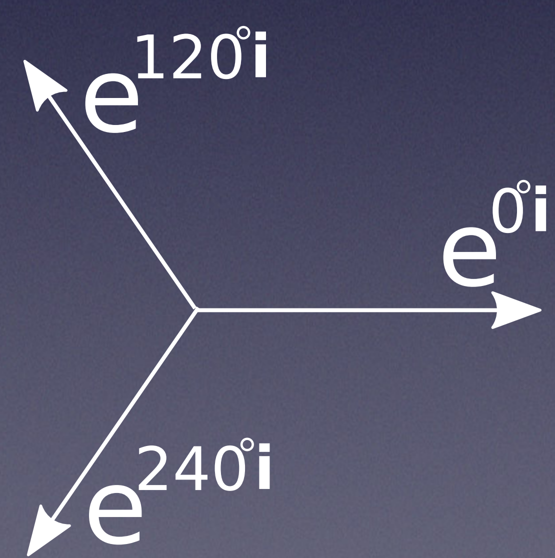
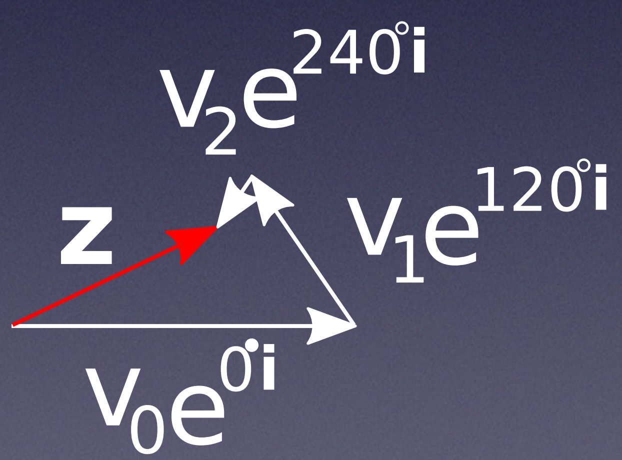
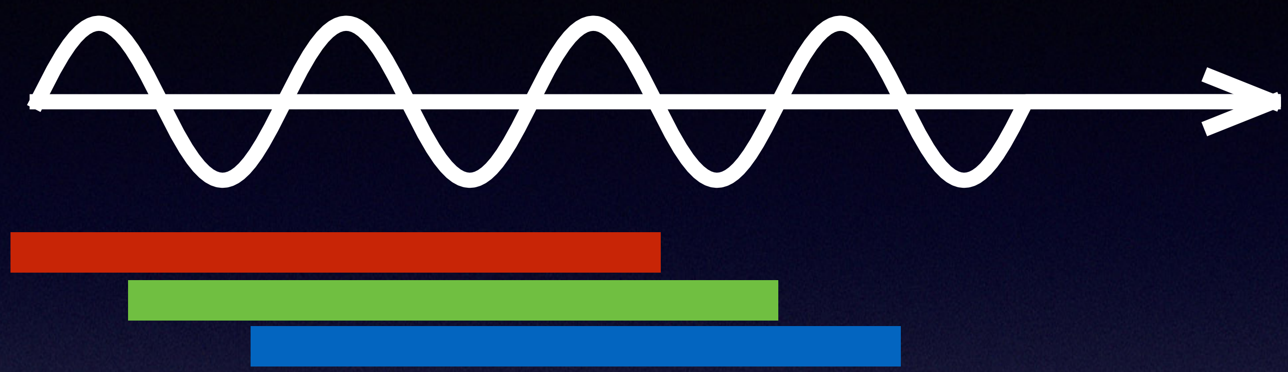




Time-of-flight cameras



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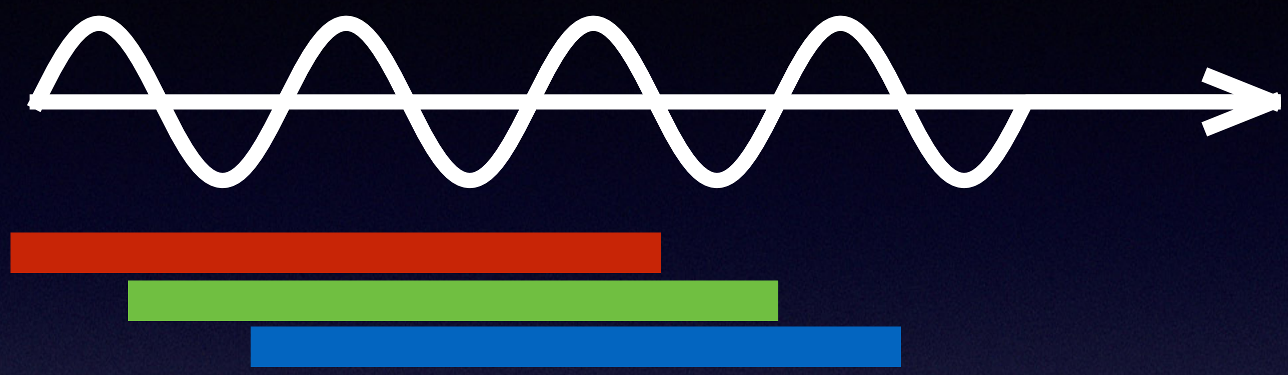
- This is done using a vector summation of the correlations:

$$\mathbf{z} = \sum_{k=0}^{2} v_k e^{-120^\circ \cdot \mathbf{i}k} \qquad \hat{\phi} = \arg \mathbf{z}$$

$$\hat{a} = |\mathbf{z}|$$

Time-of-flight cameras



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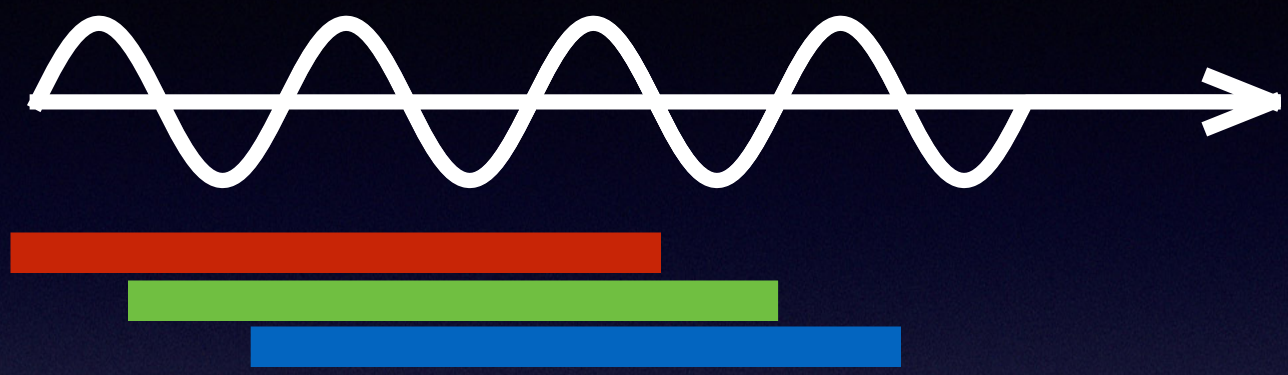
$$\mathbf{z} = \sum_{k=0}^{2} v_k e^{-120^\circ \cdot \mathbf{i}k} \qquad \hat{\phi} = \arg \mathbf{z} \qquad d = \frac{c\phi}{4\pi f_m}$$

$$\hat{a} = |\mathbf{z}|$$

Time-of-flight cameras

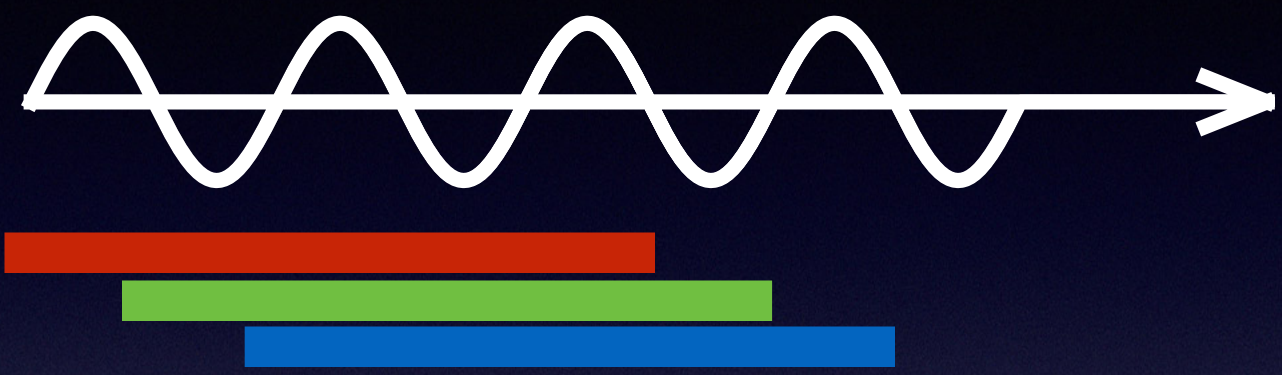


$$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$$

- For three or more correlations:

1. the amplitude $\hat{a} = |\mathbf{z}|$ will correspond to ***coherence***, i.e. we can use it to detect whether a sinusoidal signal is actually received.
2. a constant ambient offset will not matter.
3. $\hat{\phi}$ is also insensitive to attenuation of $r(t)$.

Time-of-flight cameras



$r(t) = I_r(1 + \cos(2\pi f_m t - \phi))$

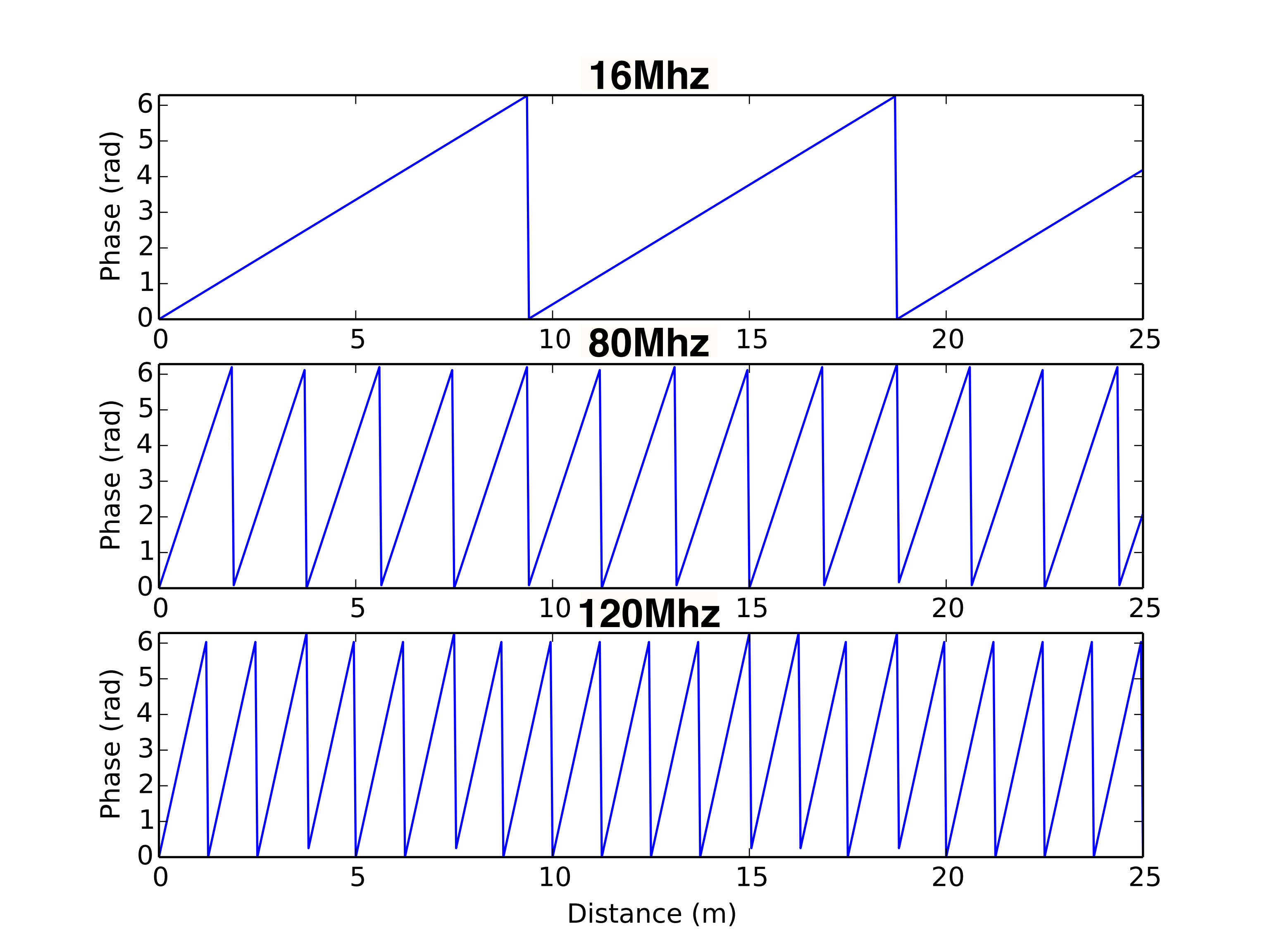
- The decoded depth $\hat{\phi}$ will have a ***periodic ambiguity***:

$$d = \frac{c\phi}{4\pi f_m} \qquad \phi \approx \hat{\phi} + 2\pi n \quad n \in \mathbb{Z}$$

Kinect v2 depth decoding

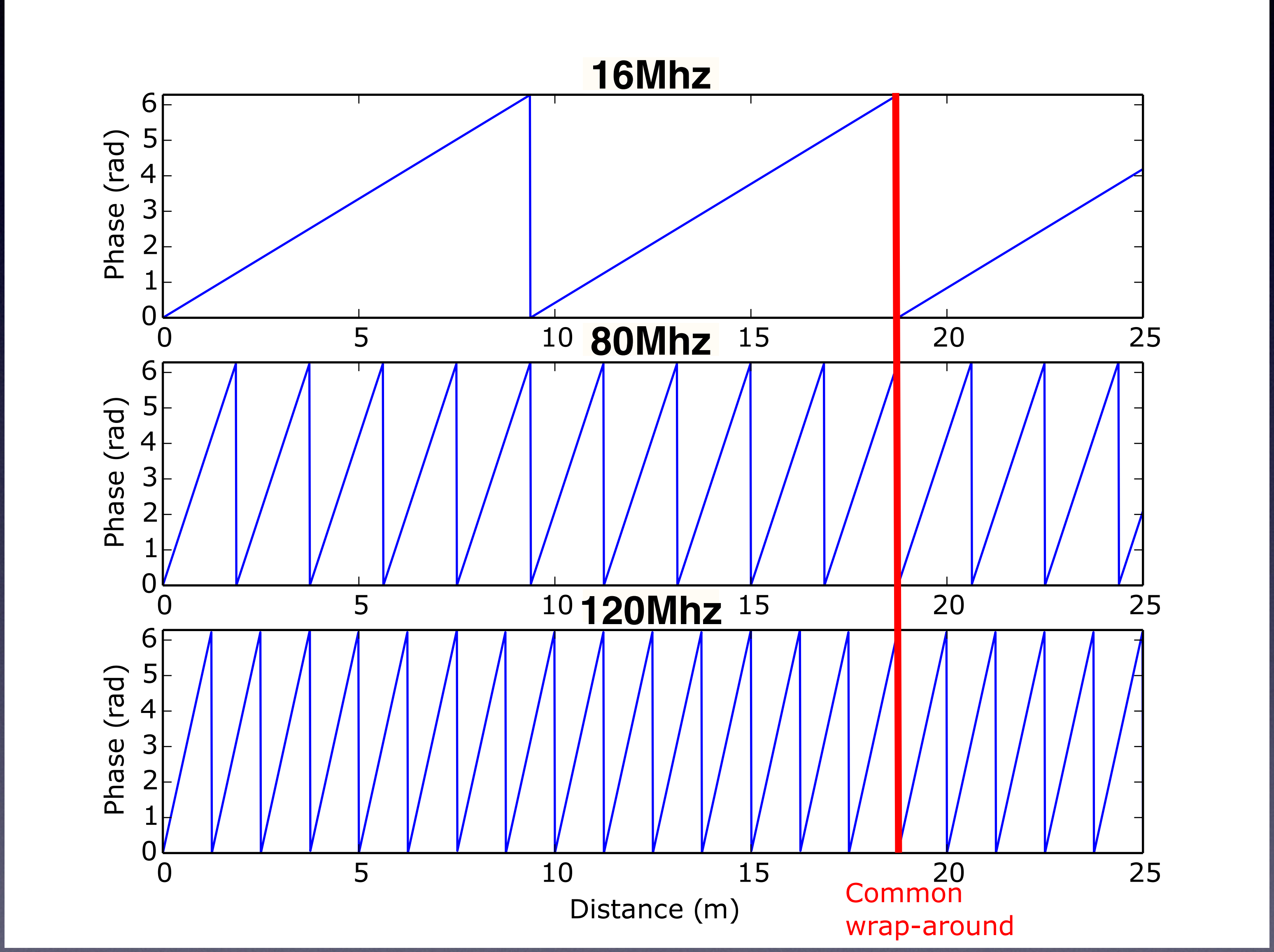
- Distance travelled: $d = \dfrac{c\phi}{4\pi f_m}$
- Problem: $\phi \approx \hat{\phi} + 2\pi n \quad n \in \mathbb{Z}$
- As a fix, Kinect v2 uses three modulation frequencies.
- This means 3 phases x 3 frequencies = 9 images are recorded for each depth frame.

Kinect v2 depth decoding

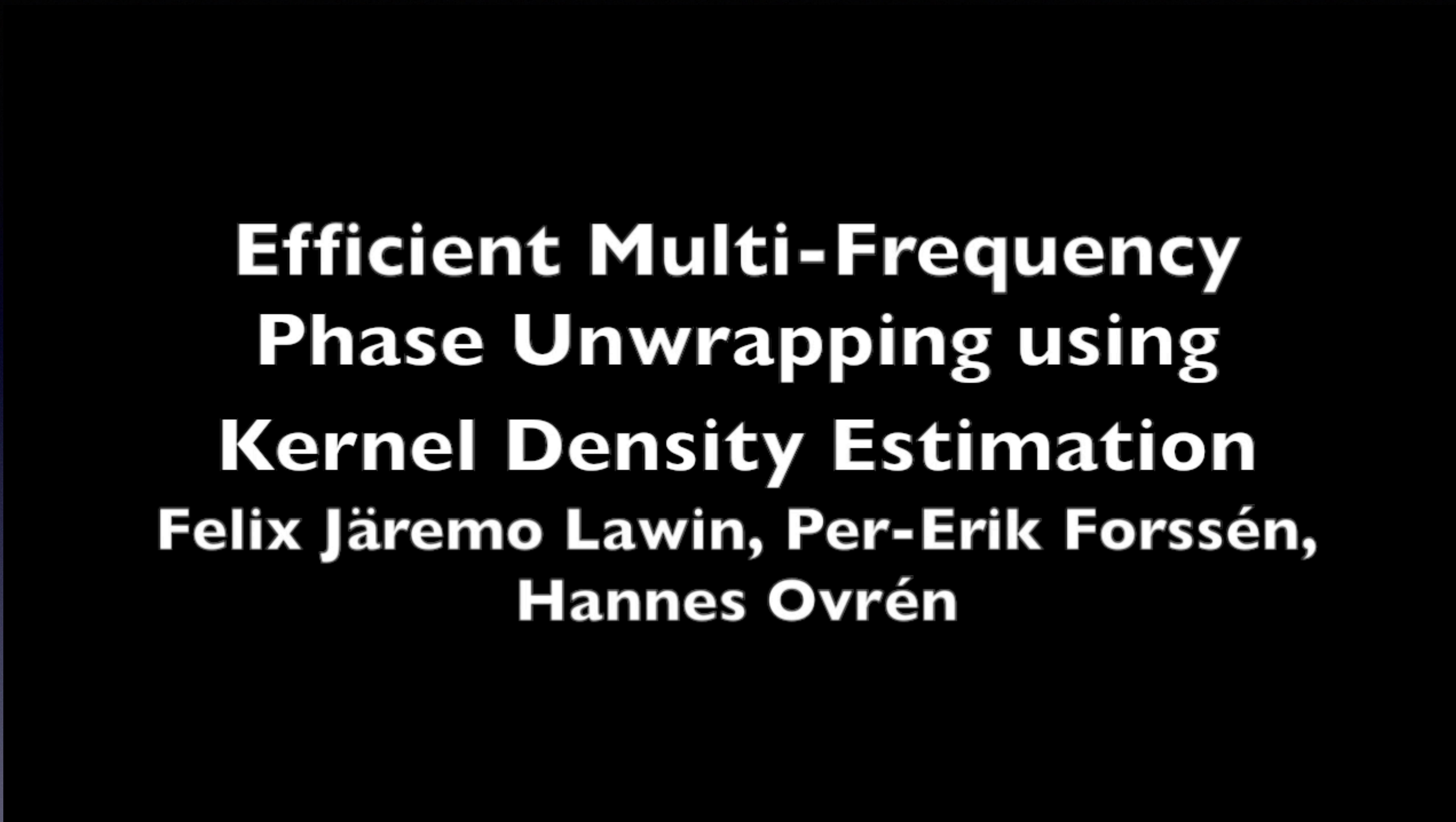


- Three modulation frequencies

Kinect v2 depth decoding



- Felix Järemo Lawin, Per-Erik Forssén, Hannes Ovrén , ”Efficient Multi-Frequency Phase Unwrapping using Kernel Density Estimation”, **ECCV16**, October 2016



- ECCV16 Video Example

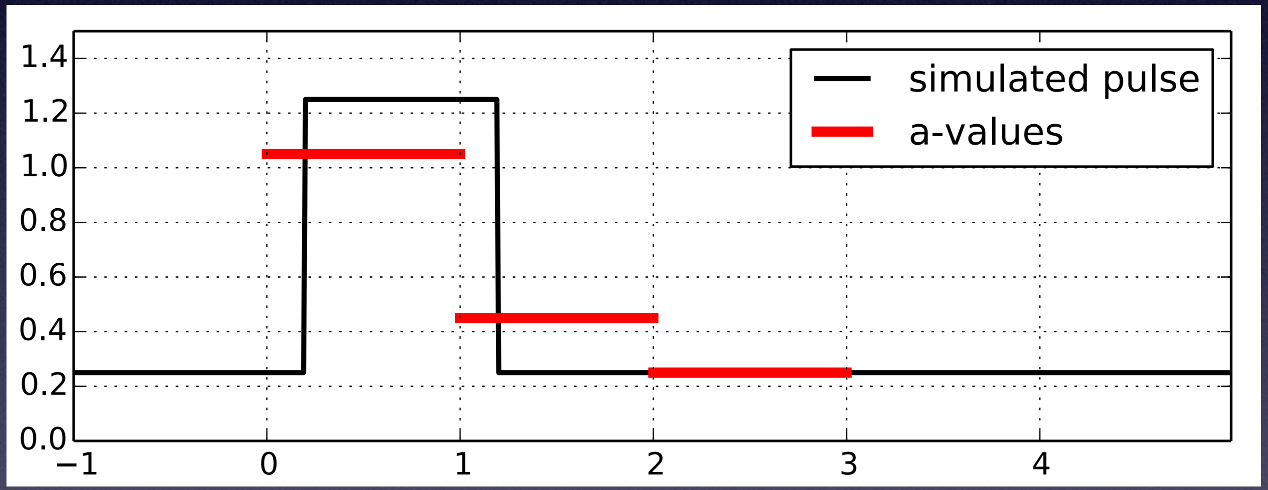
Pulsed ToF decoding

- Decoding for pulsed ToF (aka. Flash LIDAR)

Fotonic (Magna/Veoneer)
Prototype ToF camera

Pulsed ToF decoding

- Decoding for pulsed ToF (aka. Flash LIDAR)

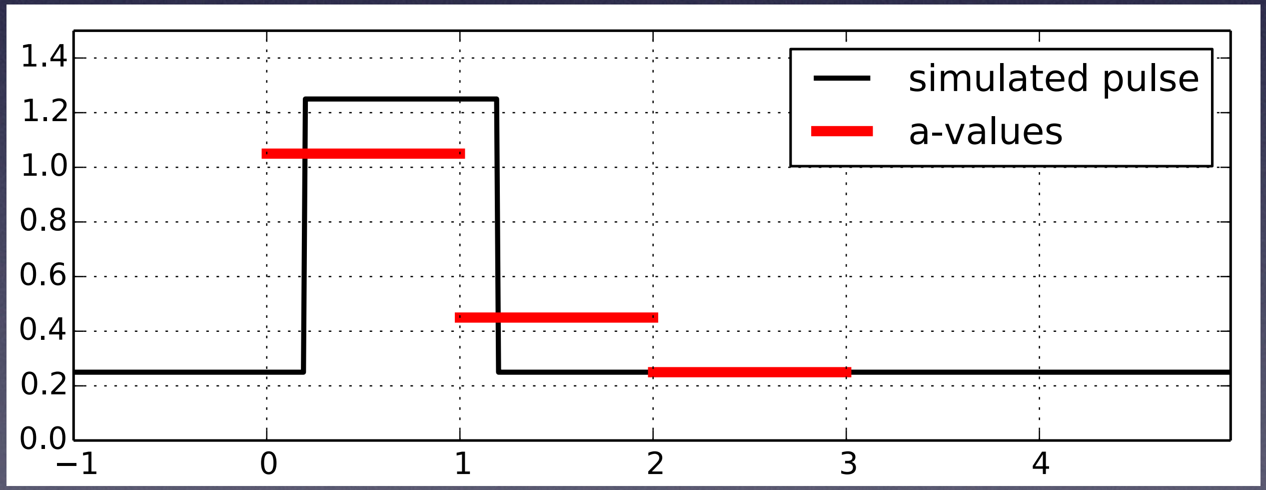


Fotonic (Magna/Veoneer) Prototype ToF camera

- Measure the reflected light in three short intervals (with length equal to light pulse length)

Pulsed ToF decoding

- Decoding for pulsed ToF (aka. Flash LIDAR)
- Assuming pulse in [0,2] interval:



$$b = a_2$$ (ambient light estimate)

$$m = \sum_{k=0}^{2} a_k - 3b$$ (pulse energy)

Pulsed ToF decoding

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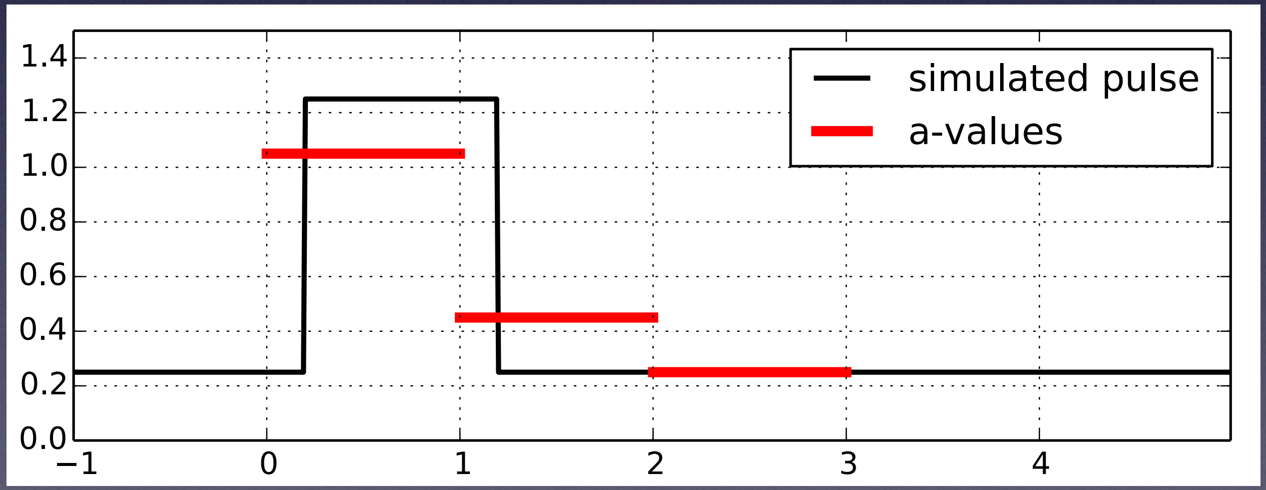


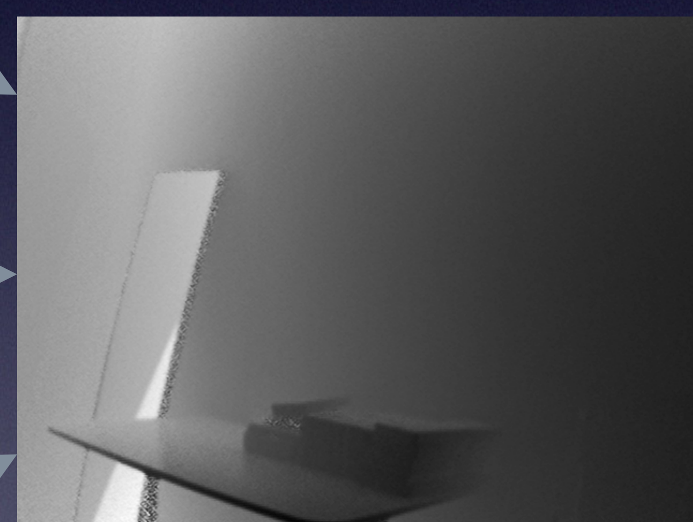
$$b = a_2$$ (ambient light estimate)

$$m = \sum_{k=0}^{2} a_k - 3b$$ (pulse energy)

$$t_d = (t_1 - t_0)\frac{a_1 - b}{m}$$

Pulsed ToF decoding

sensor images



Decoded depth

More general expression:

$$b = \min(a_0, a_1, a_2)$$

$$m = \sum_{k=0}^{2} (a_k - b)$$

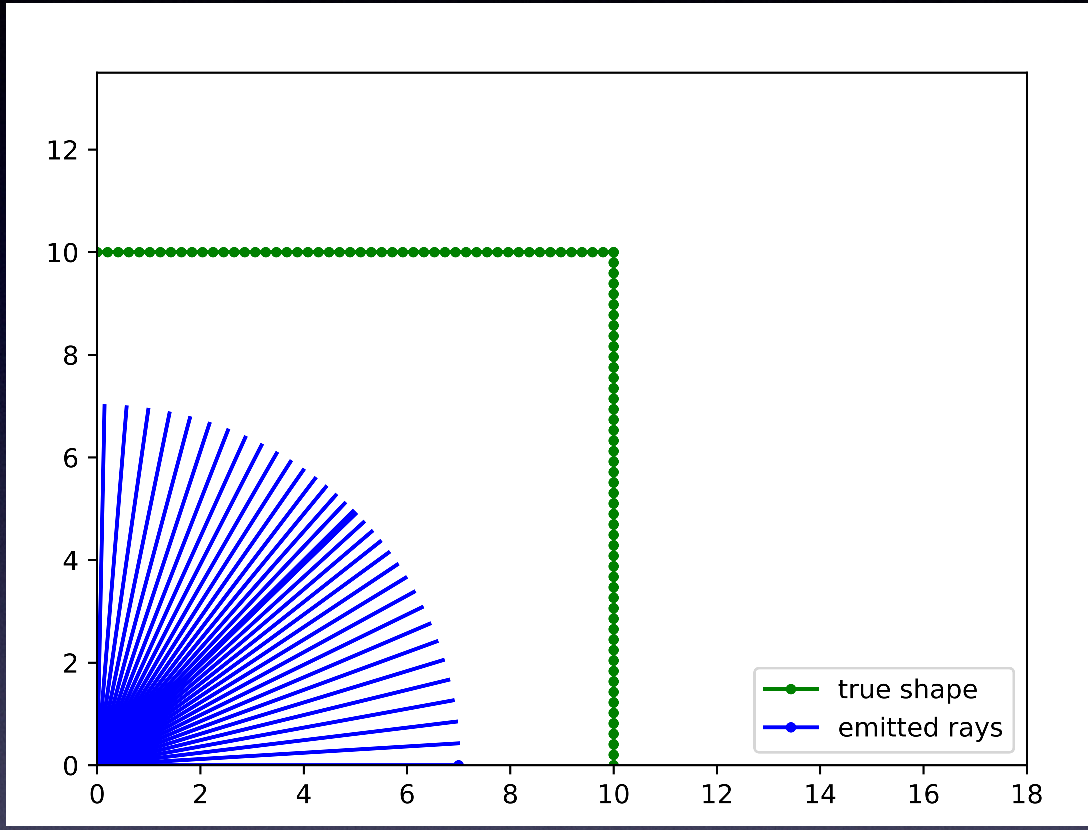
$$t_d = \frac{1}{m} \sum_{k=0}^{2} t_k (a_k - b)$$

Multipath interference

- Many light rays emitted at once.

- ⇒ depth distortion

  on concave surfaces.



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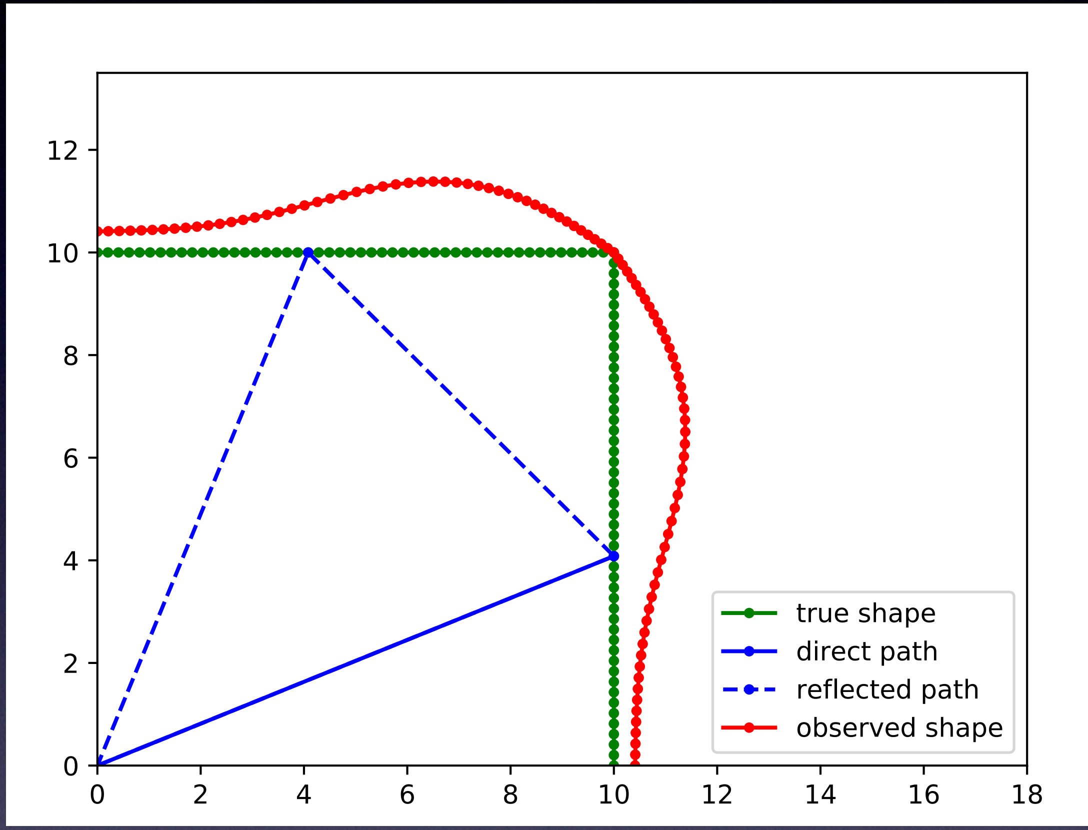


- Obtained depth is an intensity-weighted average of the path lengths (a material dependent distortion).

Multipath interference

- To reduce Multipath interference (MPI), Flash Lidar sensors often introduce line or column scanning.

- MPI can still occur along the line though.

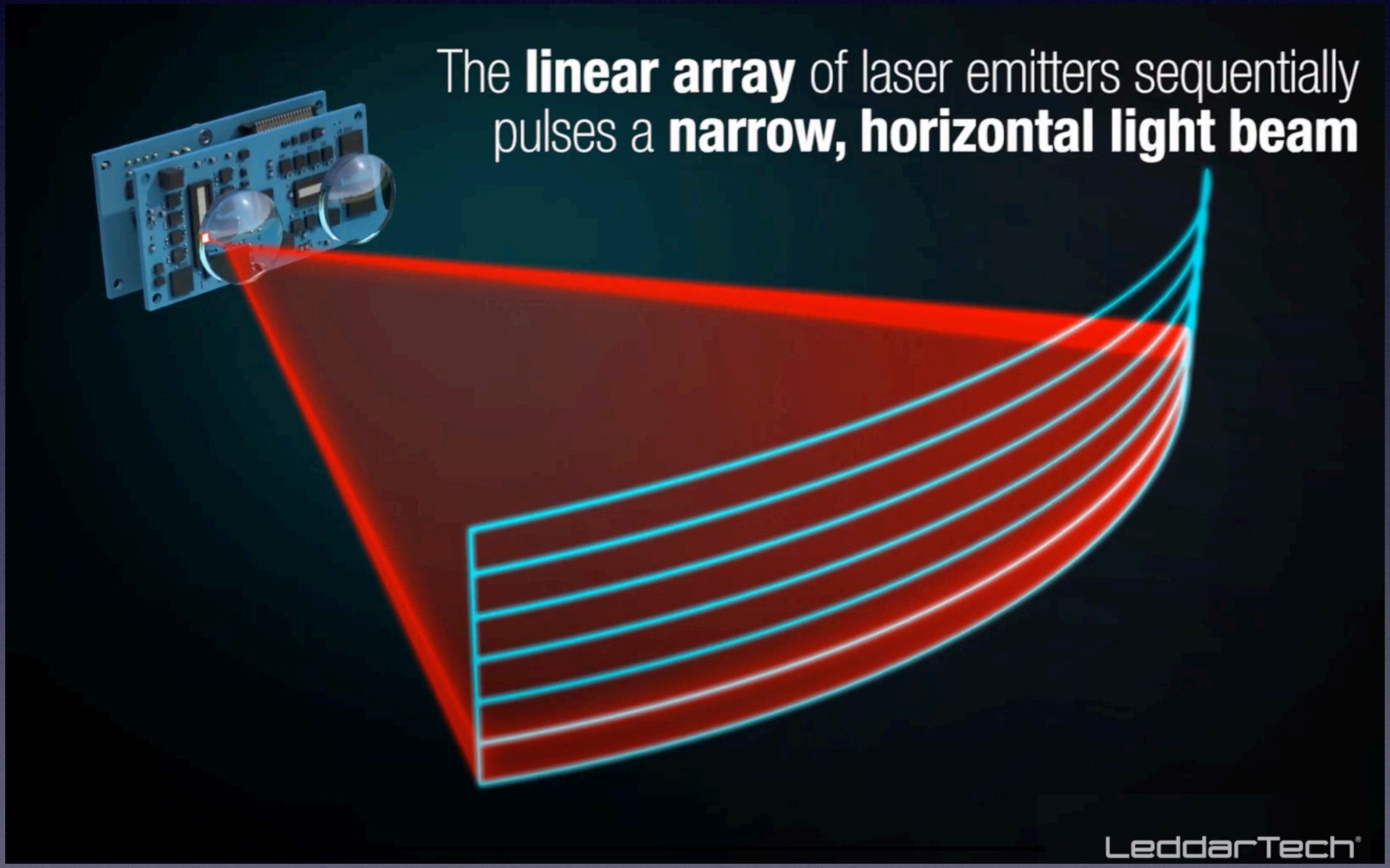


Image source: LeddarTech

Depth sensors for automation

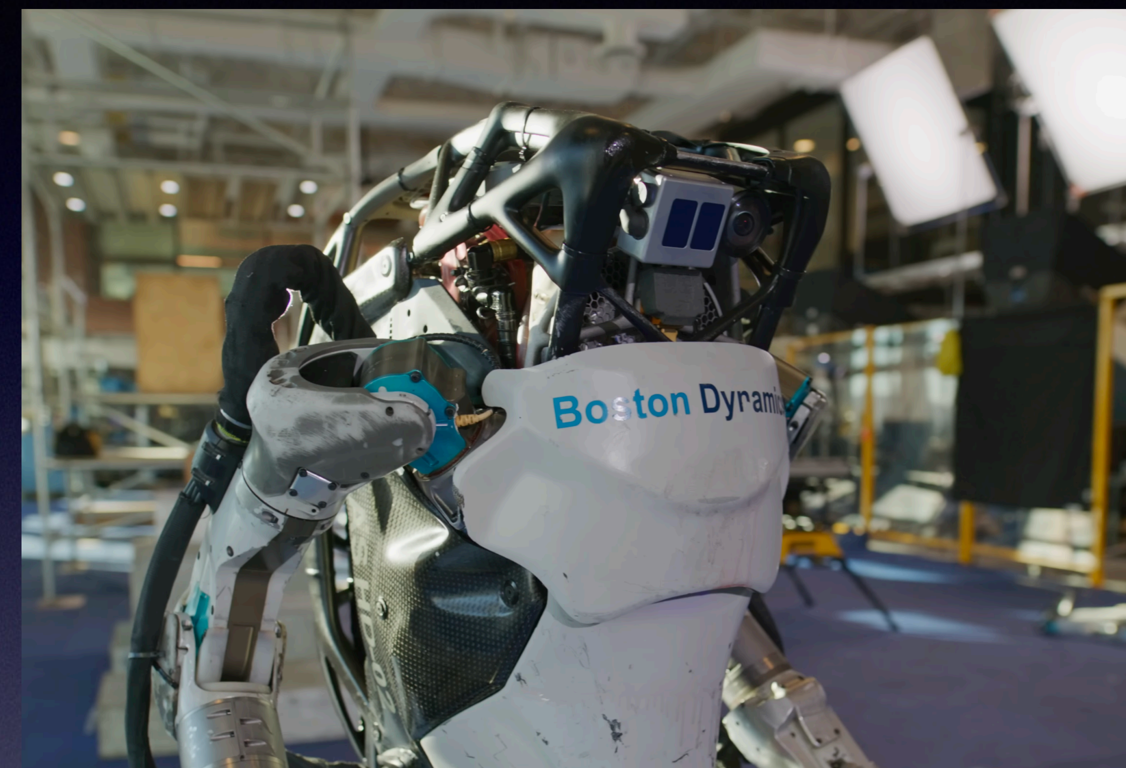
- In warehouse automation SICK LMS and other line-scanning sensors have been the first hand choice.
- As they are line scanning they only observe obstacles in one plane.
- For obstacle avoidance, full 3D is safer.

Source: SICK TiM571

- ToF cameras or Flash LIDAR have long range and are relatively inexpensive (e.g. MS Azure Kinect).

Depth sensors for automation

Source: ifm electronic

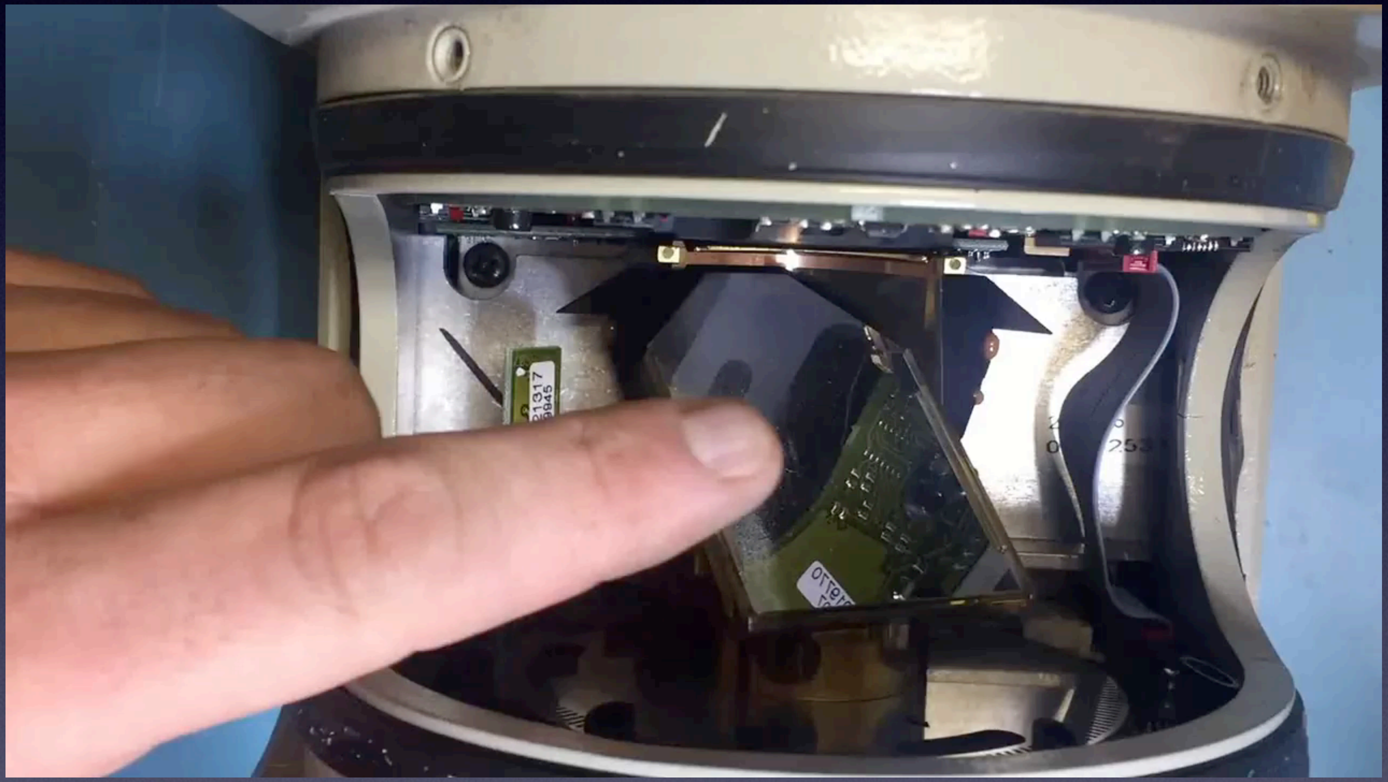


Source: Boston Dynamics

- Autonomous cleaning robots is another application (this one is for Deutsche Bahn).
- Also humanoid automation (BD Atlas)

2D Lidar

- SICK LMS291

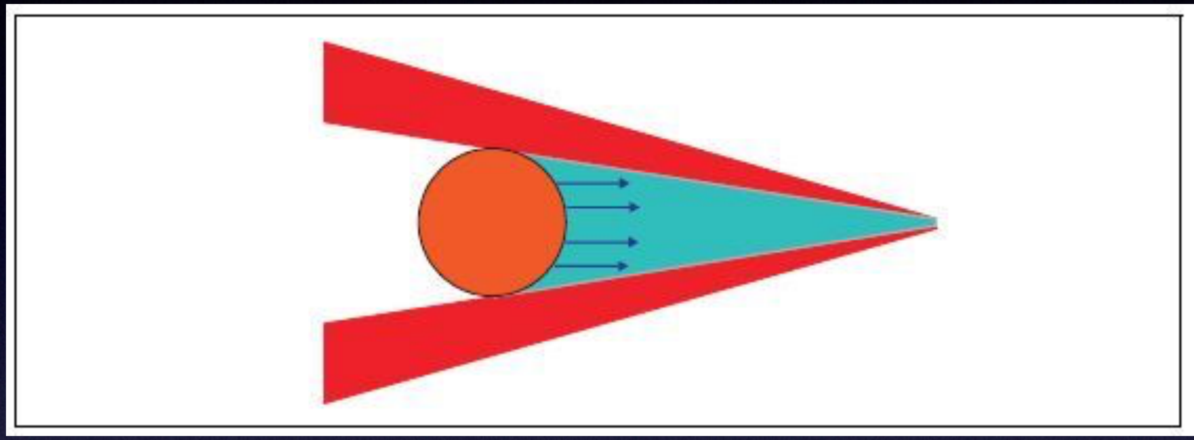


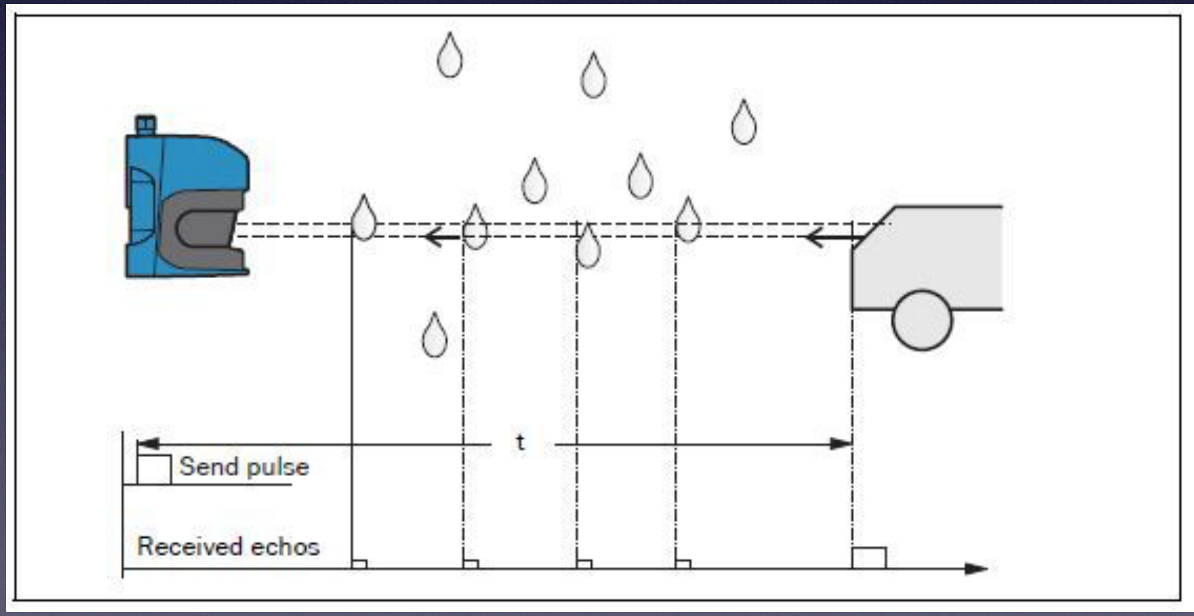
Source: David Kohanbash:
http://robotsforroboticists.com/sick-lms-lidar-teardown/

2D Lidar

- Uses direct ToF measurement using an accurate clock that is read out triggered by an SPAD detector.

- Challenges for Lidar:
  - Dot size grows with range.
  - Small objects cause multiple echos. Mitigated on recent sensors using ***multiple return***: Two or more echoes and their strengths are recorded in each direction.
  - Motion distortion (discussed later)





Source: SICK

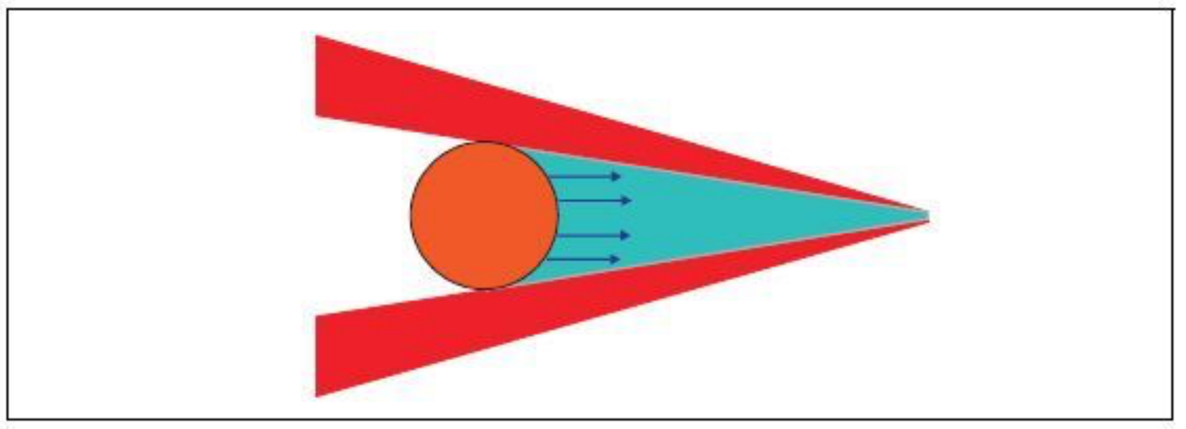
2D Lidar

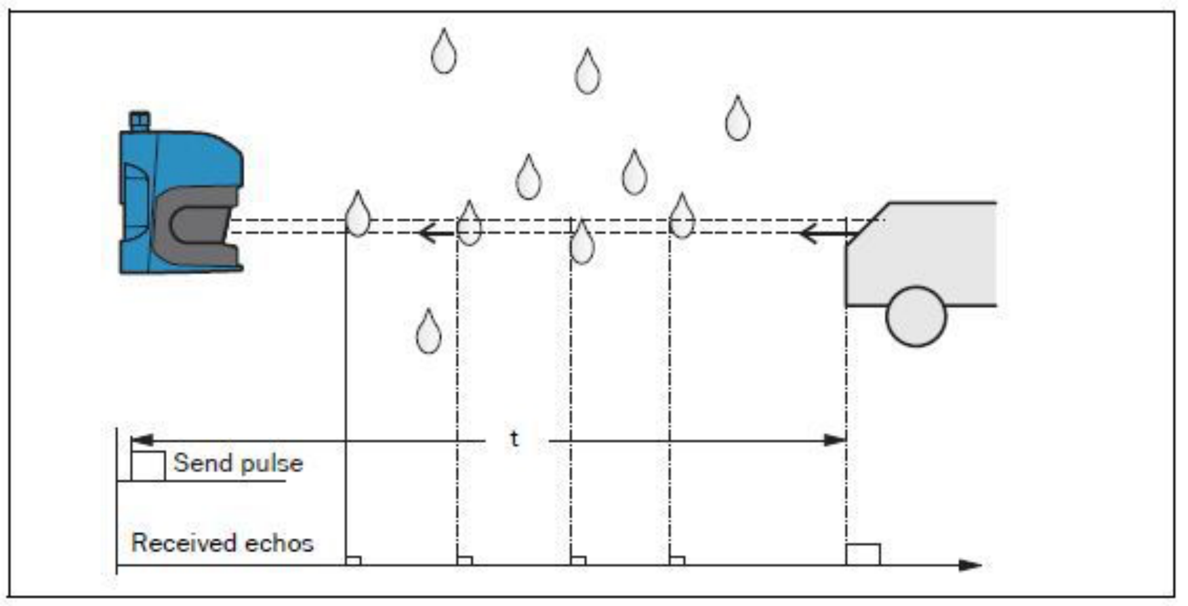
- Uses direct ToF measurement using an accurate clock that is read out triggered by an SPAD detector.

- Advantages with Lidar:
  + One light direction at a time
  ⇒ no multipath interference.

  + Less sensitivity to ambient light

  + Longer range, compared to ToF and structured light

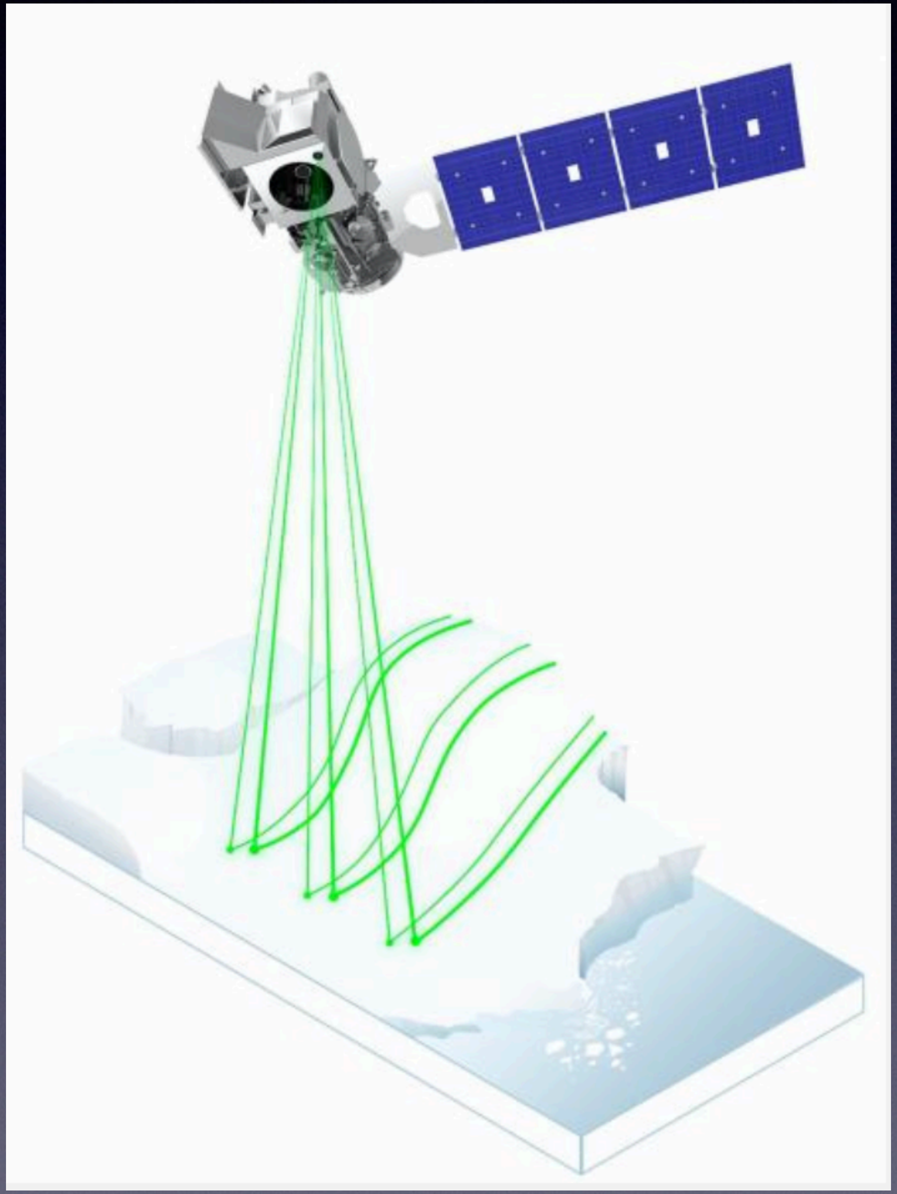




Source: SICK

2D Lidar

- LIDAR even works from space!
- NASAs ICESat-2 is used to map Antarctica’s ice. (has high reflectance)
- Swath of 6 beams
- ICESat2 has cm range accuracy (but a large spatial average)
- For more detailed elevation maps stereo is used (Maxar in Linköping)



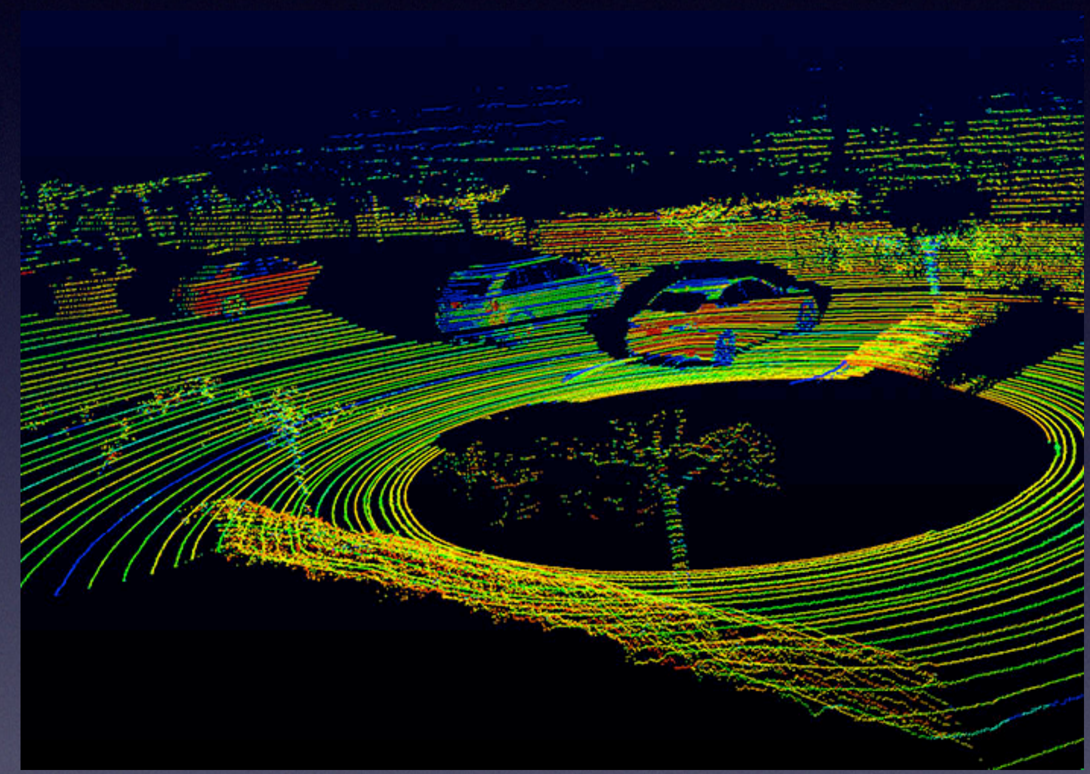
2D Lidar

- 3D Lidar evolved from 2D Lidars mounted on cars
- SICK LMS at 2005 DARPA challenge

Stanford ”Stanley”. The car that won the 2005 DARPA challenge

3D Lidar

- **2007-now:** Velodyne HDL-64E

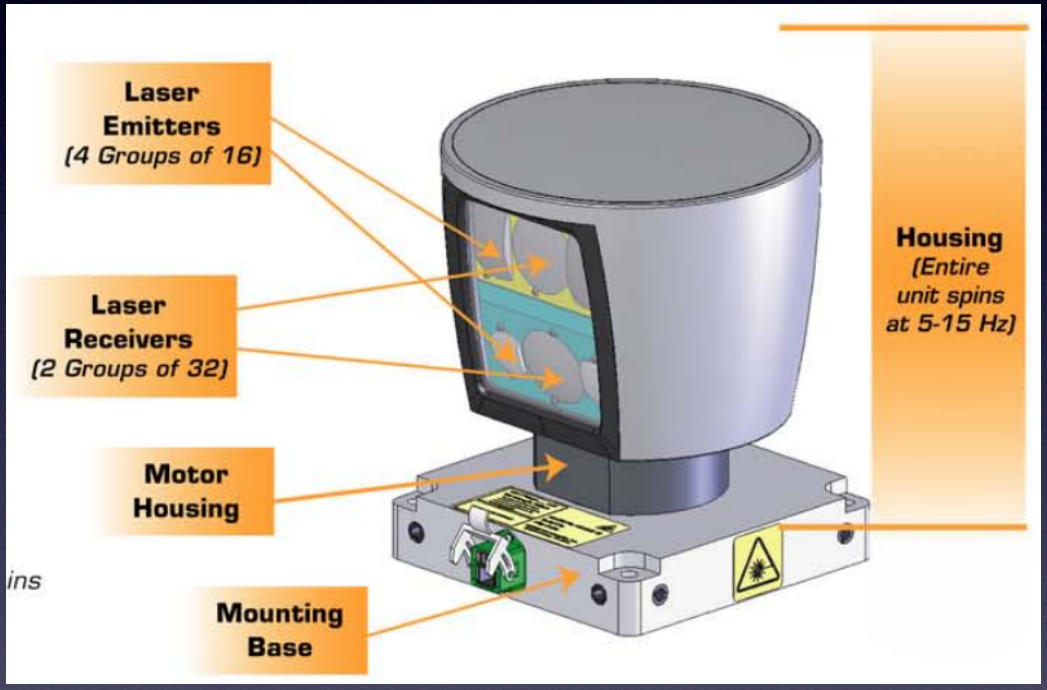


https://www.cvlibs.net/datasets/kitti/ https://velodynelidar.com/hdl-64e.html

- A 64-line ToF sensor that scans 360°

3D Lidar

- The Velodyne principle: rotate entire sensor package

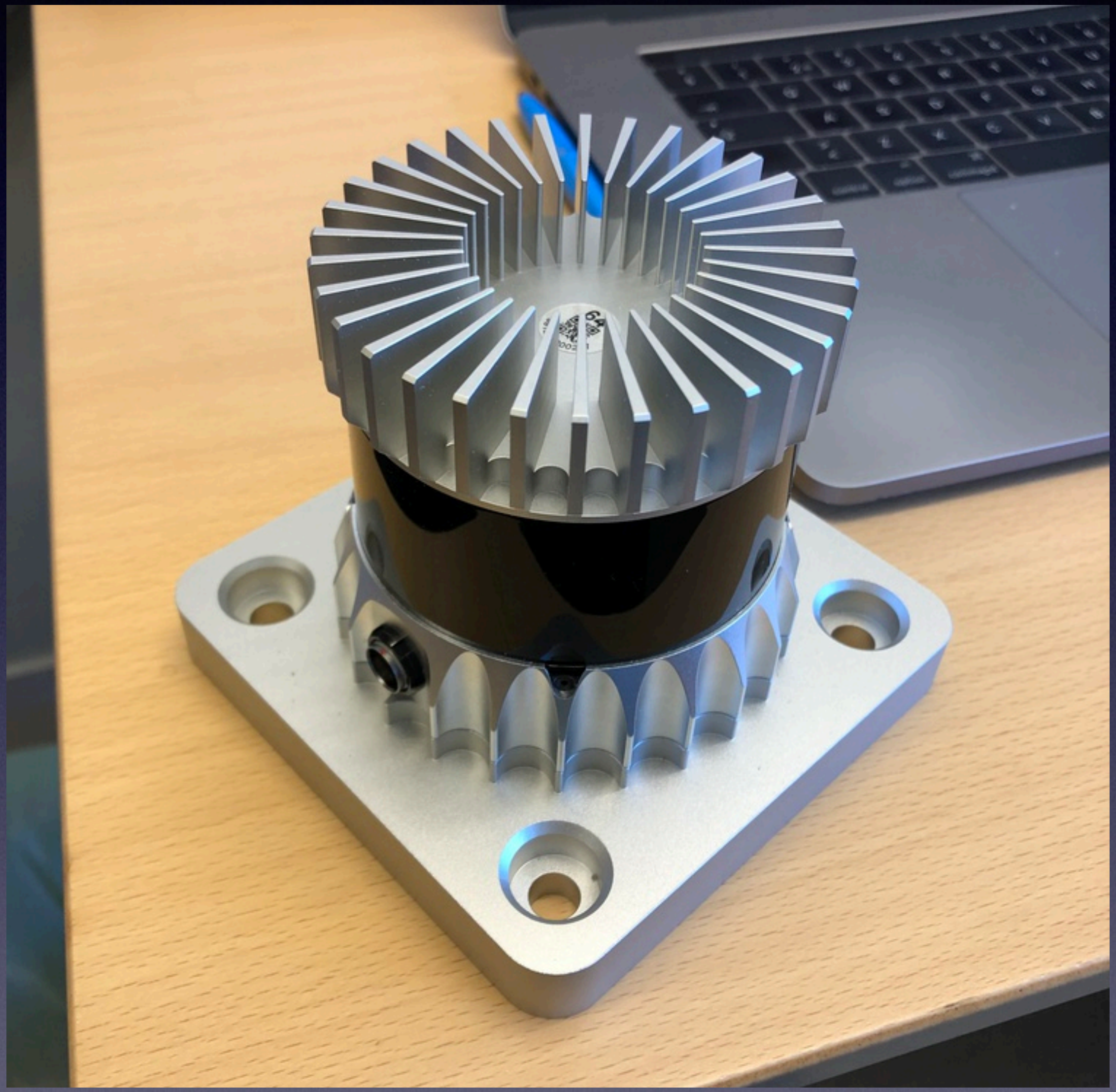


Source: Velodyne

Source: Matt McFarland, https://www.youtube.com/watch?v=kIrMaPTENB0

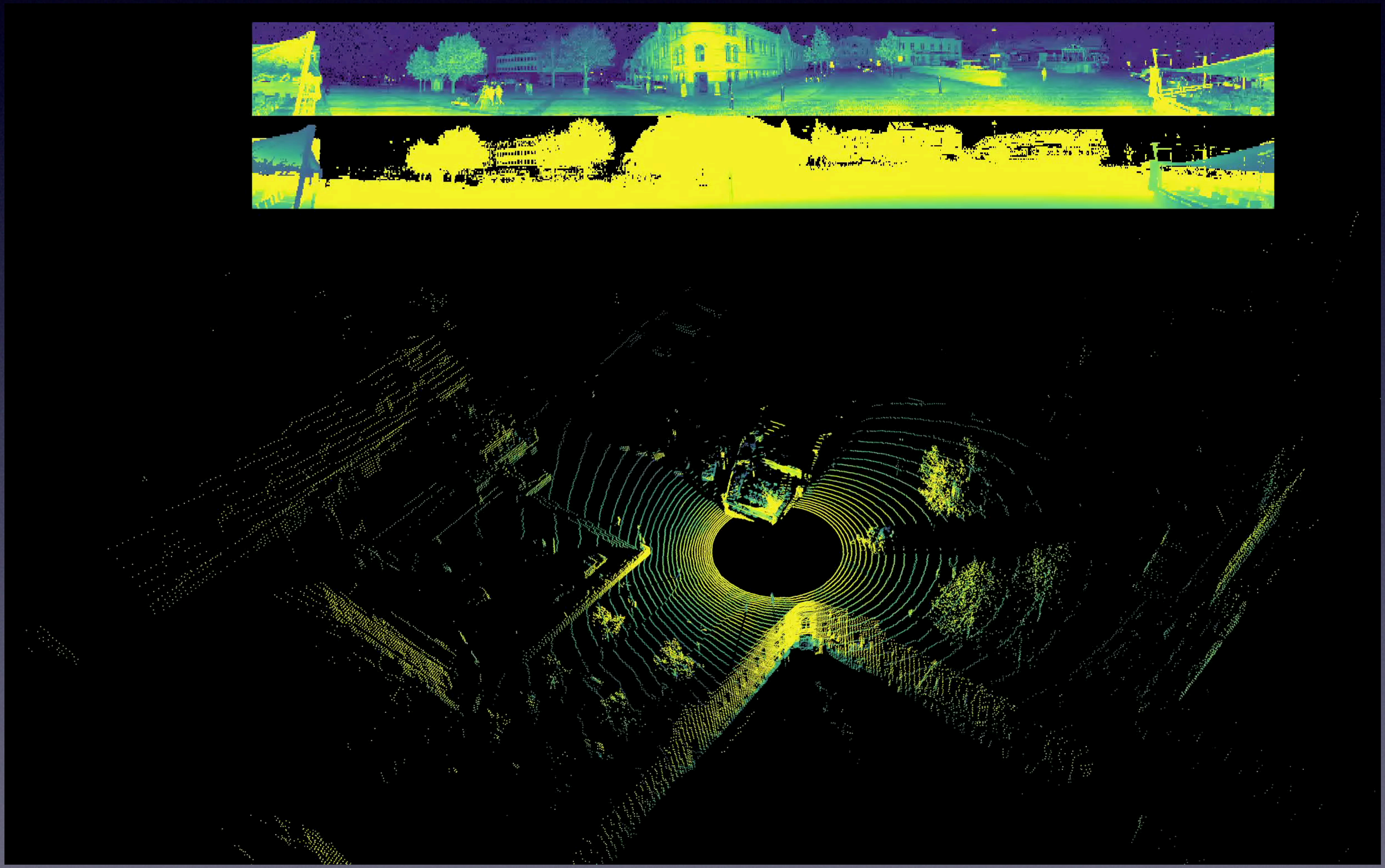
The Ouster OS-1 64

- Size WxH = 8.5x7.3cm
  Weight 396g
- 64 lines
  2048 directions @10Hz
  33.2°x 360°
- 6 axis IMU (Gyro,Acc)
  @100Hz
- Range: 105m or more.

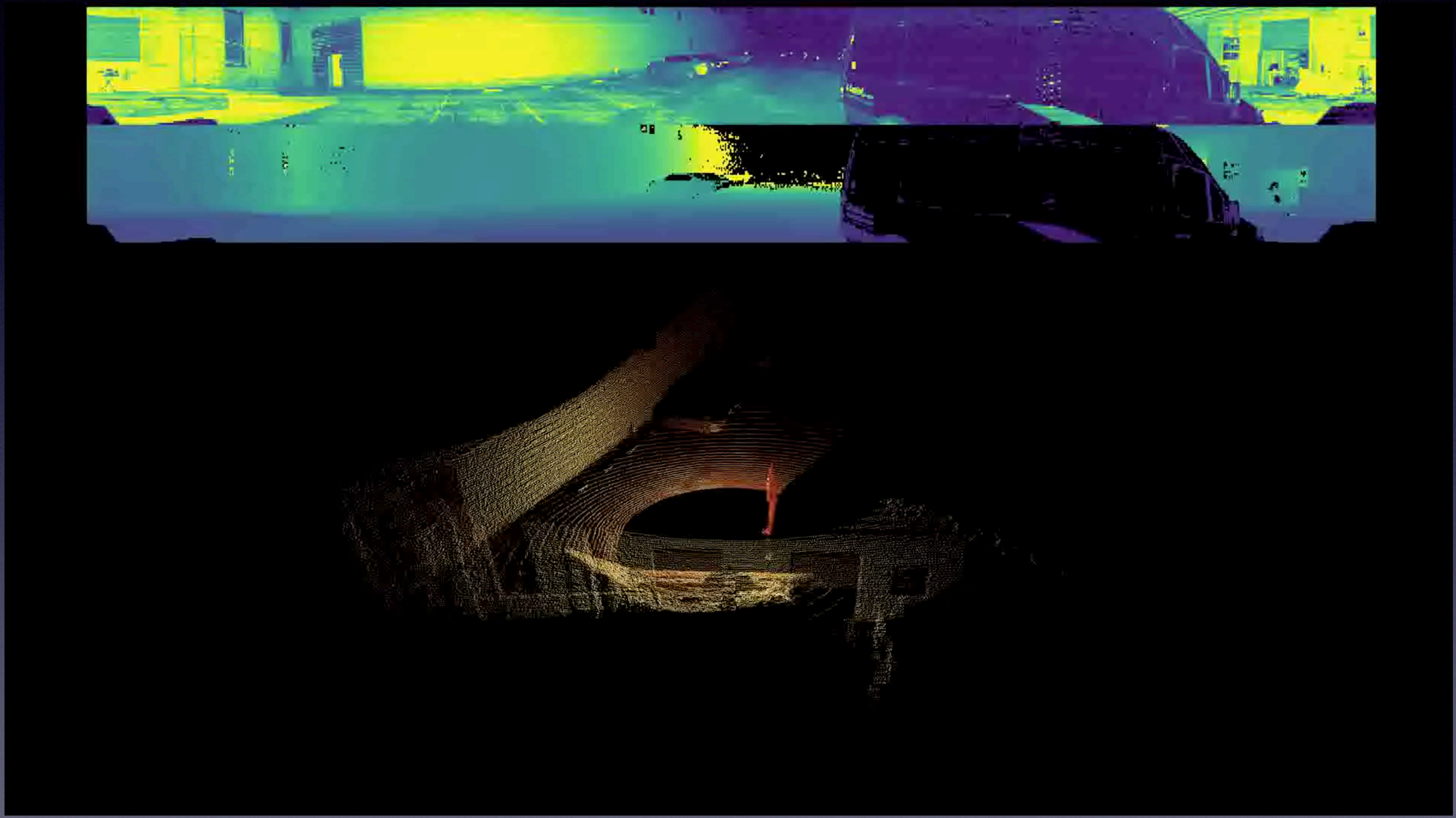


3D Lidar

- Hand-held Ouster OS1-64 Lidar in Västervik



Mapping with 3D Lidar



https://www.youtube.com/watch?v=4QYnqbO1eT0

Terrestrial Laser Scanners

- Terrestrial Laser Scanner (TLS)
- Sensor is placed on a tripod at a number of selected locations. One scan takes several minutes.
- Used when accuracy is important, and speed less so. mm range resolution. E.g. 1200 x 2048 points per scan (pan,tilt).
- Many different variants, but usually:
  - a tilting mirror for vertical resolution
  - a step motor for horizontal resolution
  - a colour camera gives a spherical panorama, and an RGB value for each depth point.

Image source: Wikimedia Commons
https://commons.wikimedia.org/wiki/File:Lidar_P1270901.jpg

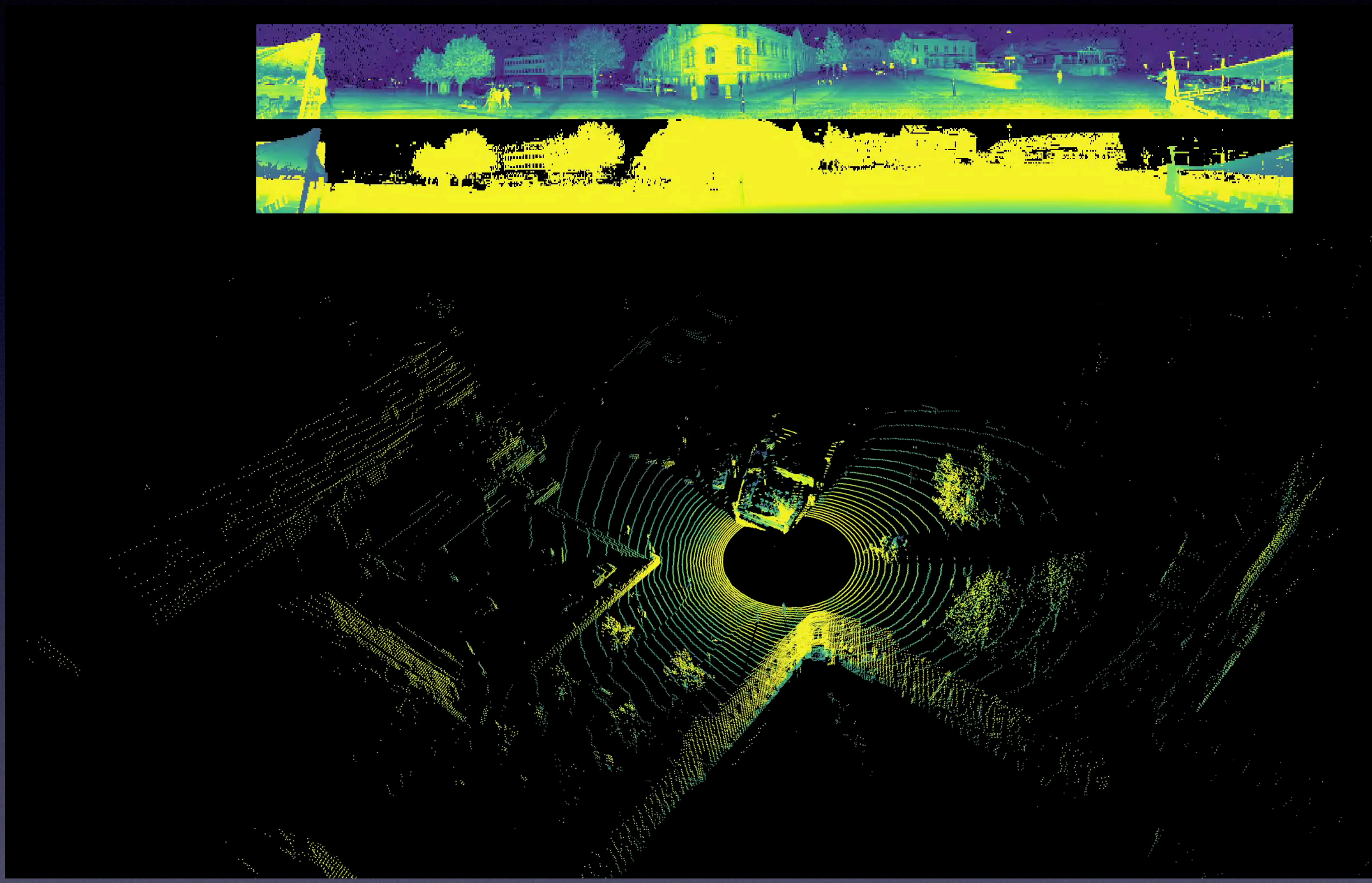
Terrestrial Laser Scanners

https://www.laserscanning-europe.com/en/servicesdevices/terrestrial-laser-scanners

- The different scans are then stitched together using Point Set Registration.
- Applications include: Forensic scene documentation, Archeaology, Digital Twins of Industrial installations, Civil Engineering, Surveying.

From range to 3D

- The output from the OS-1 Lidar is a ***reflectance image*** (top) with 64 x 2048 pixels i_{kl}, and a ***range image*** (middle) with pixels r_{kl}.



- The ***point cloud*** (bottom) is calculated from these and sensor parameters.
- Note the wobble in the video, we will now analyze this.

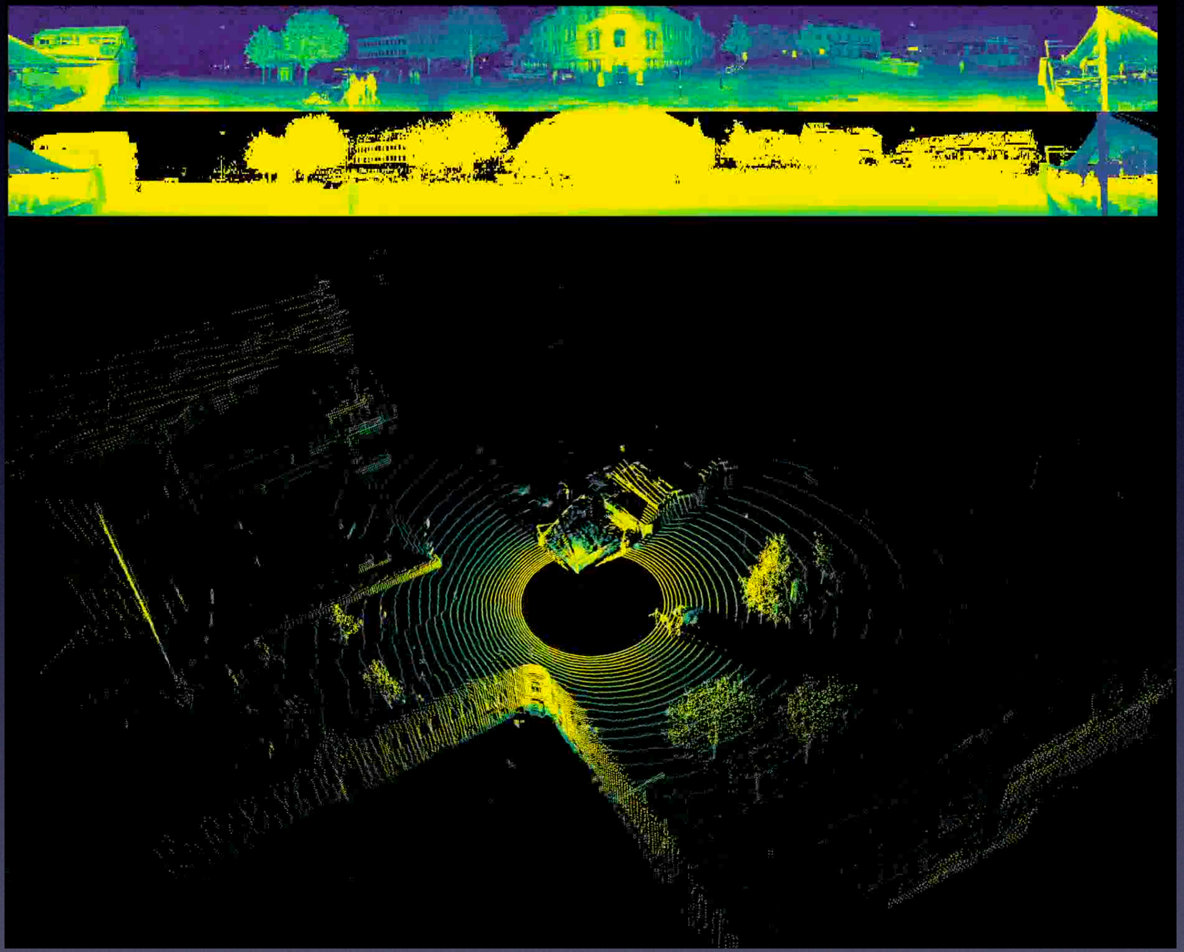
From range to 3D

- To unpack the ***range image*** r_{kl} to points in 3D do:

$$\mathbf{X}_k^{\text{raw}}(t_l) = r_{kl}\hat{\mathbf{x}}_k$$

- 64 ray directions from sensor calibration table:

$$\hat{\mathbf{x}}_k = \begin{bmatrix} \cos\theta_k \cos\phi_k \\ -\sin\theta_k \cos\phi_k \\ \sin\phi_k \end{bmatrix}$$



- Next apply the sensor rotation:

$$\begin{bmatrix} \mathbf{X}_k^{\text{car}}(t_l) \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R}(t_l) & \mathbf{0} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{X}_k^{\text{raw}}(t_l) \\ 1 \end{bmatrix}$$

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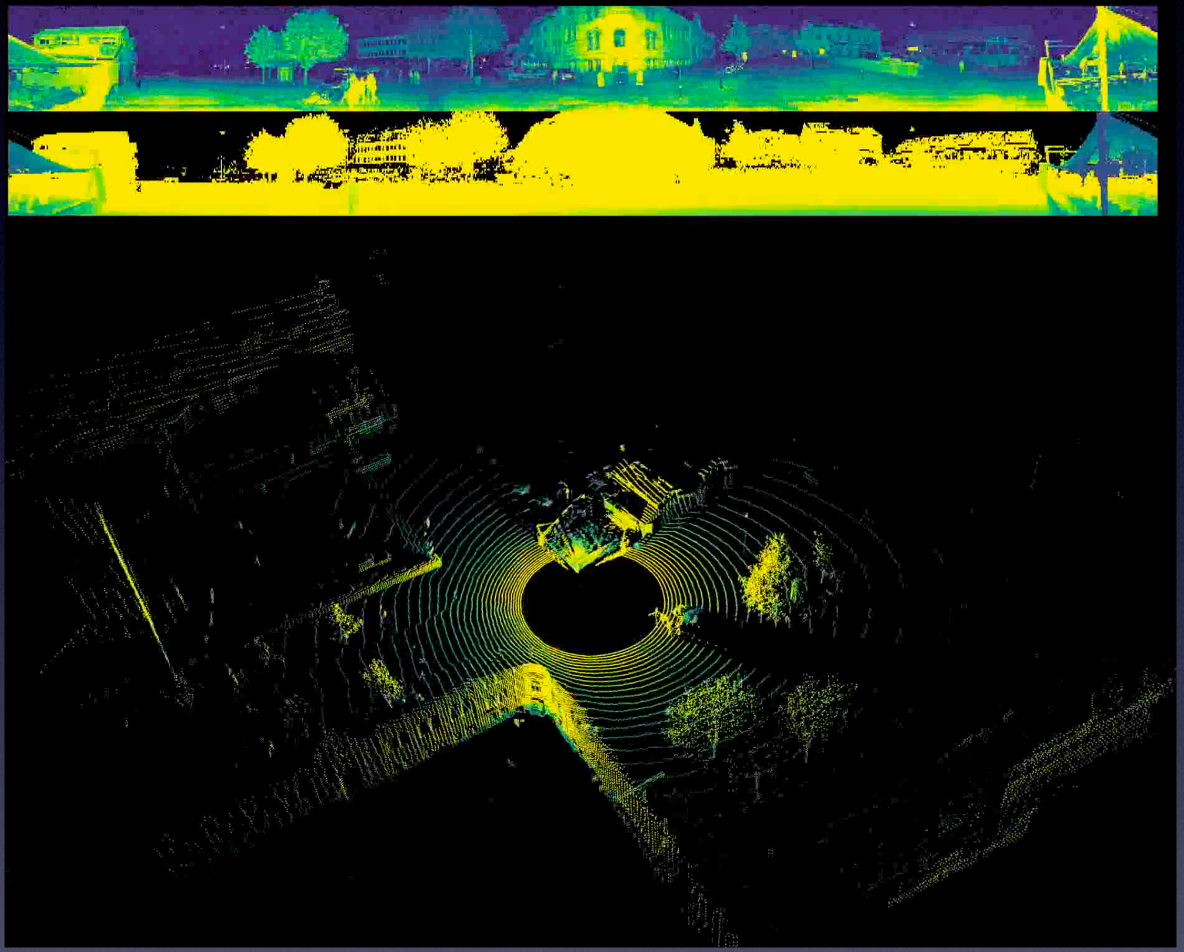


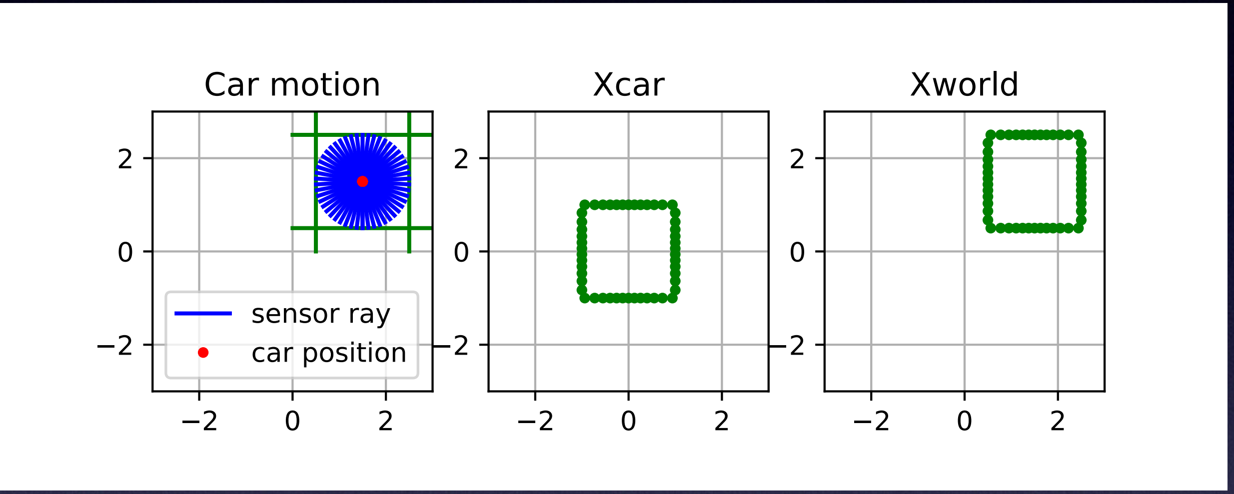
- Next apply the sensor rotation:

$$\begin{bmatrix} \mathbf{X}_k^{\mathrm{car}}(t_l) \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R}(t_l) & \mathbf{0} \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{X}_k^{\mathrm{raw}}(t_l) \\ 1 \end{bmatrix}$$

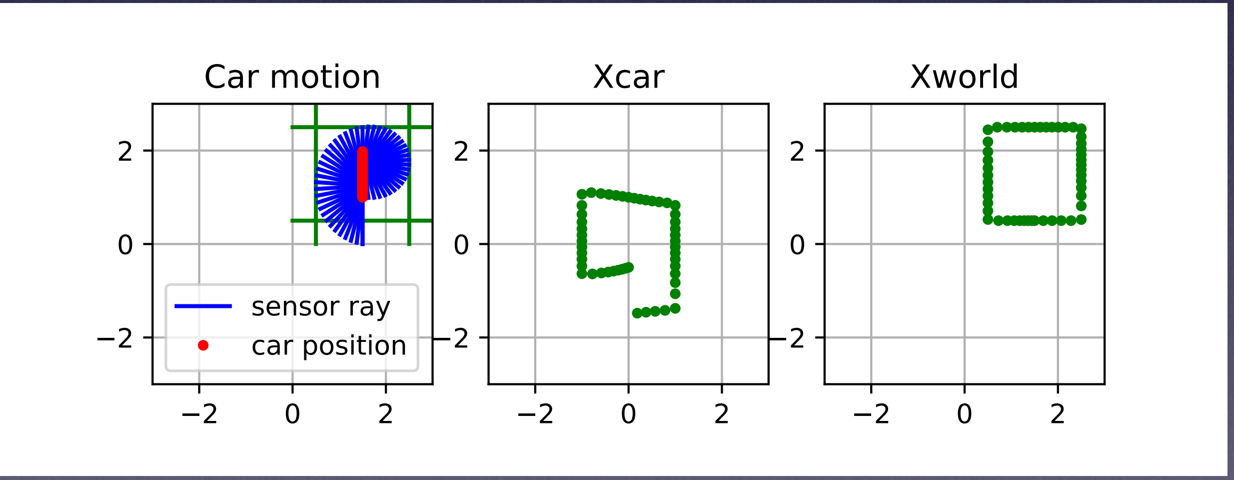
Note:
One transformation per scan line, l

Motion distortions

- Unpacking to car coordinates is sufficient in the stationary case



- But we get motion distortions if the car itself is also moving



- These can be corrected if we know the car motion.

Motion distortion correction

- A car motion estimate $(\mathbf{R}(t), \mathbf{p}(t))$ can be obtained from the IMU (accelerometers, gyroscopes) built into the car or the Lidar. Alternatively from a preliminary scan registration.

$$\begin{bmatrix} \mathbf{X}_{\text{world}}(t) \\ 1 \end{bmatrix} = \mathbf{T}_{\text{l2i}}^{-1} \begin{bmatrix} \mathbf{R}(t) & \mathbf{p}(t) \\ \mathbf{0}^T & 1 \end{bmatrix} \mathbf{T}_{\text{l2i}} \begin{bmatrix} \mathbf{X}_{\text{car}}(t) \\ 1 \end{bmatrix}$$

- Note that the transformation from the Lidar to the IMU, $\mathbf{T}_{\text{l2i}}$ needs to be known. It is normally fixed and found through calibration.

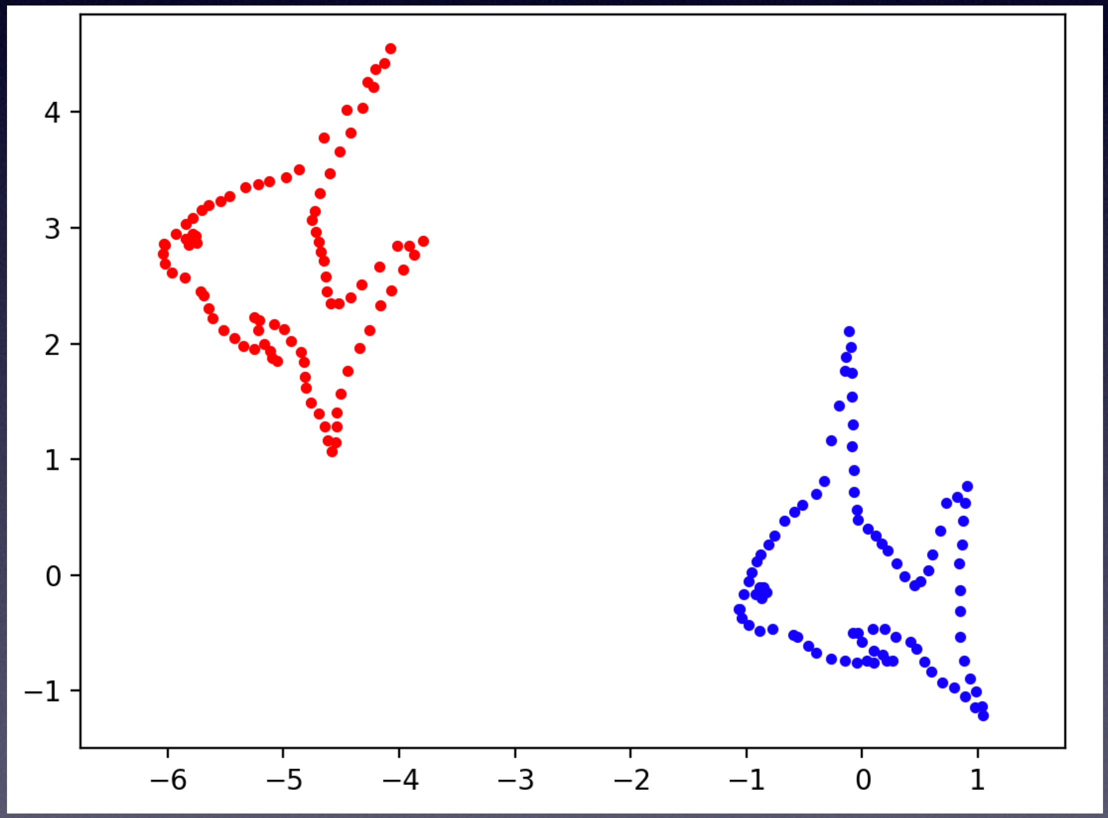
Point-set registration

- Mapping with 3D sensors use ***point-set registration***.

Goal: Find a transformation

$$\mathbf{Y}'_k = \mathbf{R}\mathbf{X}_k + \mathbf{t}$$

- That moves a set of points $\{\mathbf{X}_k\}_{k=1}^{K}$
- to be aligned with another set of points $\{\mathbf{Y}_l\}_{l=1}^{L}$

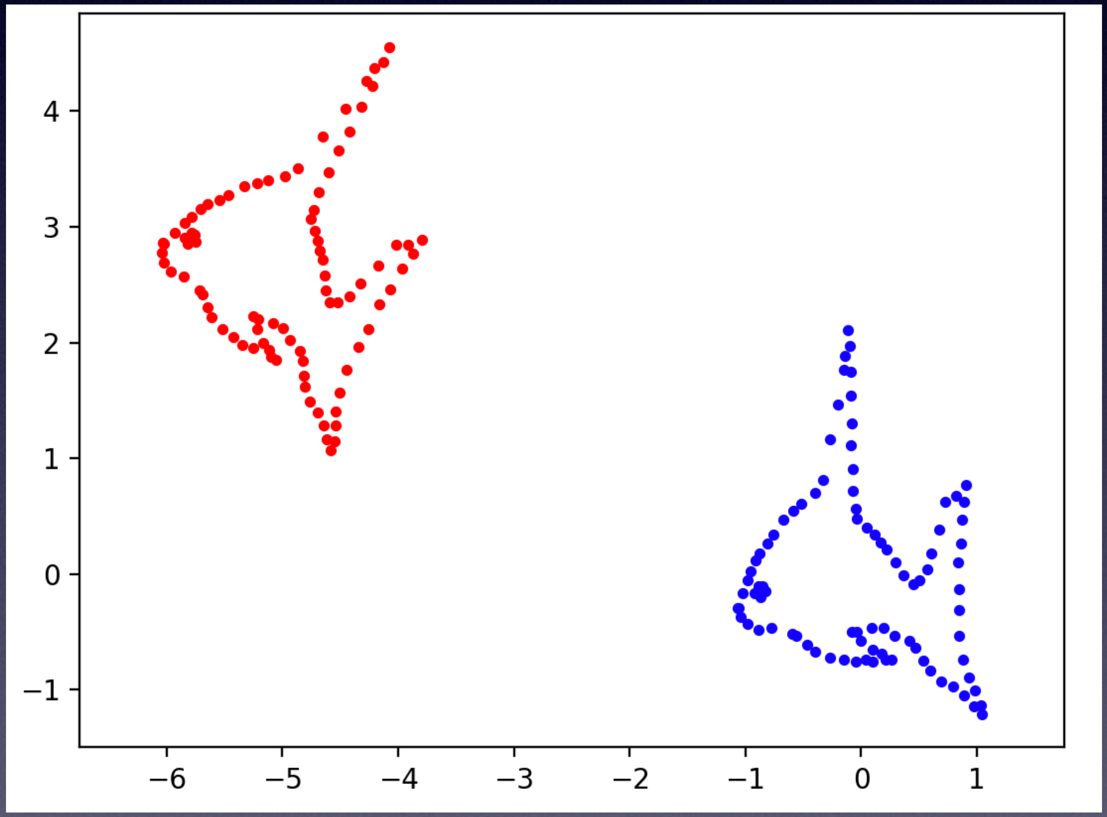


- ICP Classical method [Chen&Medioni ICRA91]

Point-set registration

- Iterated Closest Point (ICP) [Chen&Medioni ICRA91]

1. **Guess correspondence**
   For each point: find the closest point in the other set

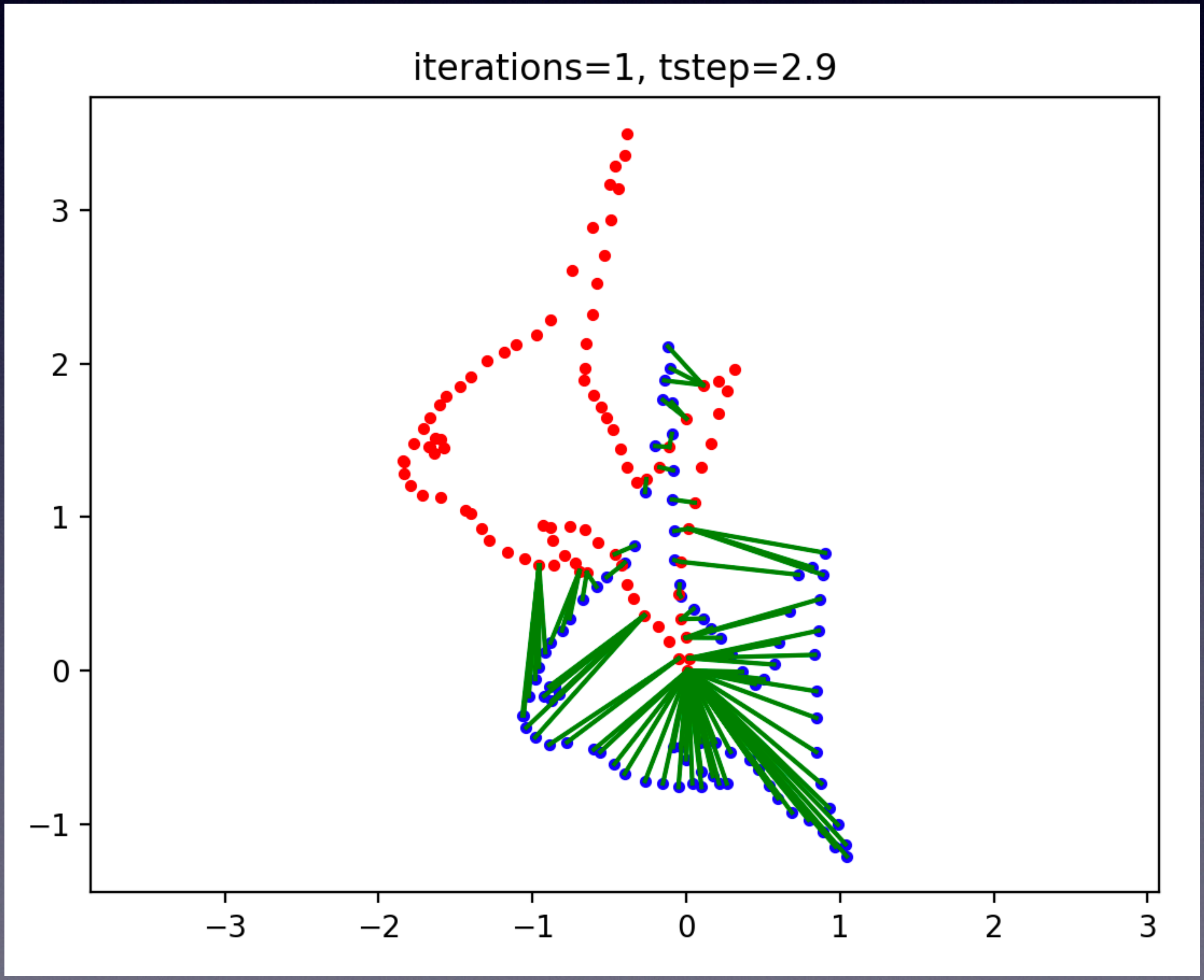


2. **Align correspondences**
   Center and solve the Orthogonal Procrustes Problem (OPP) to fint **R**, and **t**

3. **Apply transformation** and goto 1.

Point-set registration

- ICP demo 2D



Align correspondences

- Rigid point-set registration uses an Orthogonal Procrustes Problem (OPP) at its core:

$$\{\mathbf{R}, \mathbf{t}\} = \arg\min_{\mathbf{R},\mathbf{t}} \|\mathbf{X} - \mathbf{R}\mathbf{Y} + \mathbf{t}\|^2$$

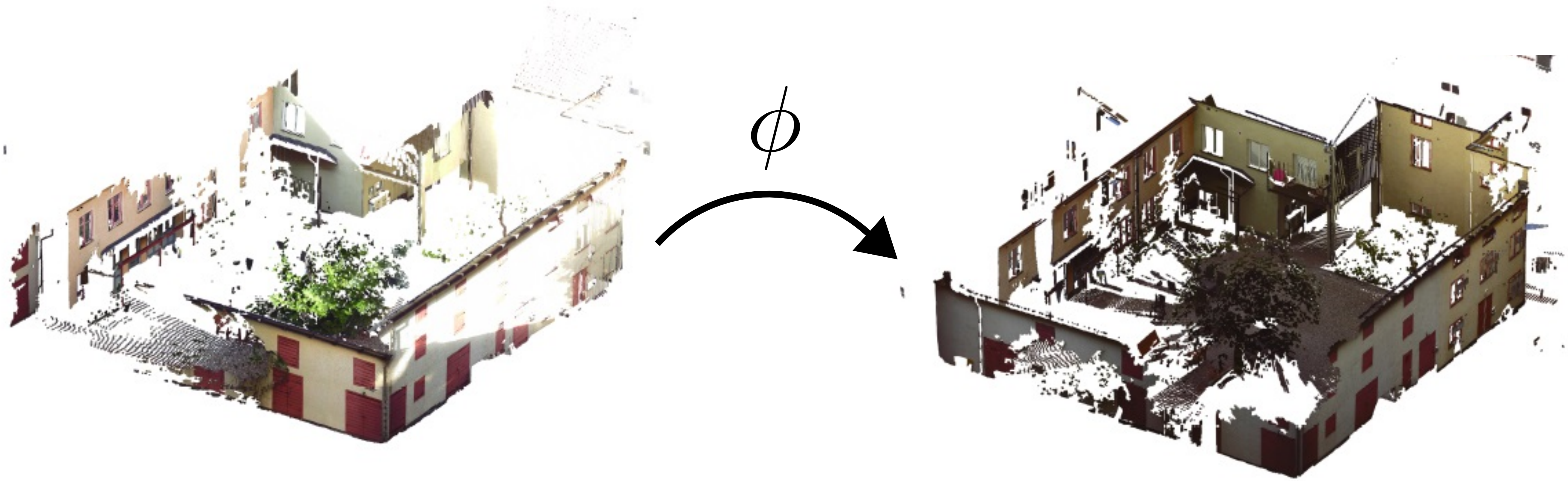
- Two point-sets **X** and **Y** (columns $\mathbf{X}_{:,n}$ are points)

$$\mathbf{X}_m = \mathbf{X} - \mathbf{X}_\mu \qquad \mathbf{X}_\mu = \frac{1}{N}\sum_{n=1}^{N} \mathbf{X}_{:,n}$$
$$\mathbf{Y}_m = \mathbf{Y} - \mathbf{Y}_\mu$$

- OPP: $\mathbf{R} = \arg\min_{\mathbf{R}} \|\mathbf{X}_m - \mathbf{R}\mathbf{Y}_m\|^2$

- Translation: $\mathbf{t} = \mathbf{X}_\mu - \mathbf{R}\mathbf{Y}_\mu$

Point-set registration



$$\phi(\mathbf{x}) = R\mathbf{x} + \mathbf{t}$$

Illustration by Martin Danelljan

Summary

- ToF cameras and Lidars both use the ***time-of-flight*** principle to sense depth.
- ToF cameras work well indoors, where they have better ***range and spatial detail*** than structured light and fringe pattern projection.
- Lidars work better outdoors, and avoid ***multipath interference***, but can instead have ***motion distortions***.
- ***Point-set registration*** (PSR) is used to create large 3D models from 3D cameras.
- Next lecture: Improvements of PSR