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# Stress Testing of Spiking Neural Network-based TDC-less dToF

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# Applications of dToF

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## Drones



## Automotive



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## Touchless UI



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## Robots



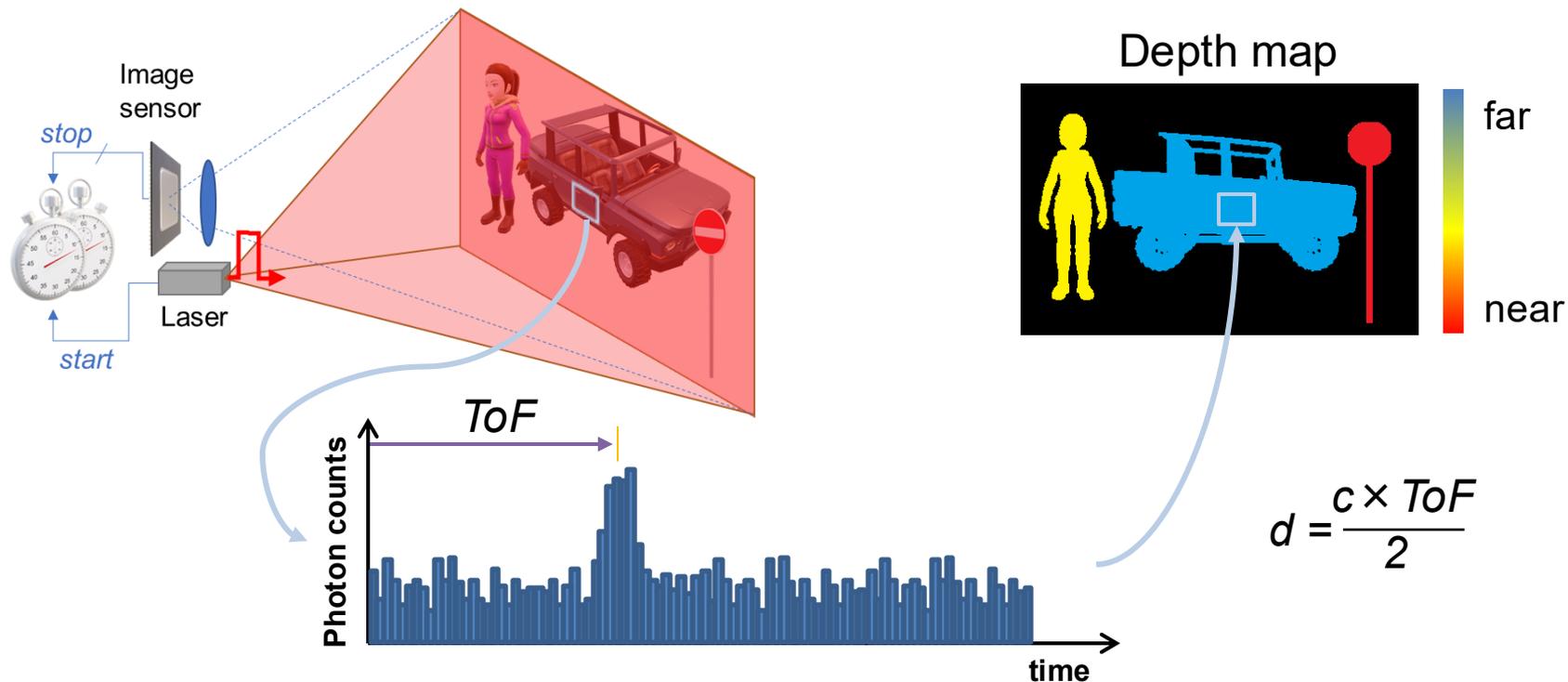
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## Smartphone

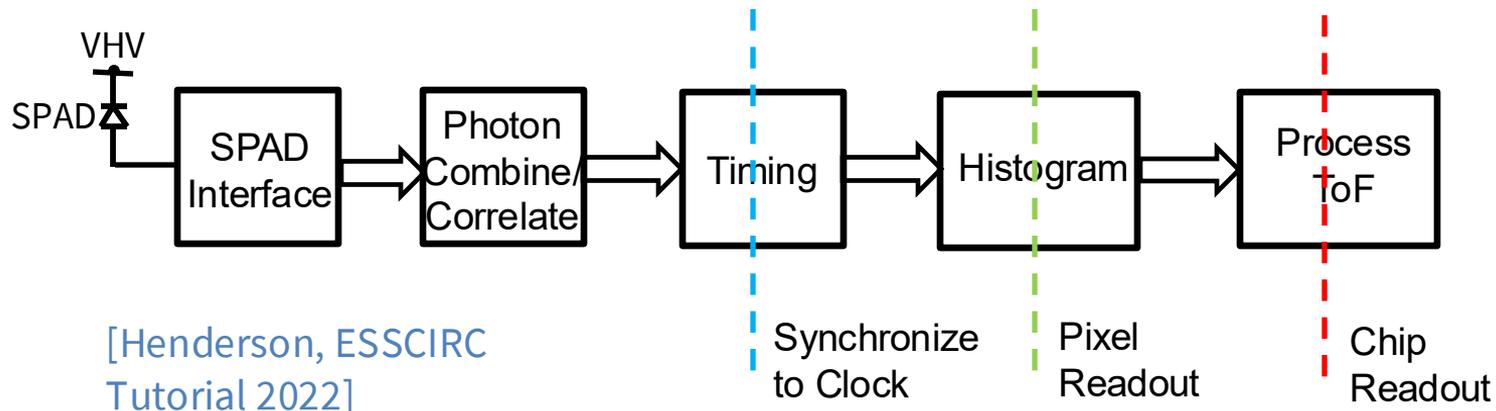


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# Solid-state dToF with SPAD



## Conventional processing pipeline



- Conventional histogramming: high speed clock and significant memory resource → **impact on power consumption, latency and scalability**
- Adaptive histogramming: reduced memory (can be integrated into pixel) but higher transmitter power, susceptibility to motion artefacts [Taneski, IEEE JLT 2022]

## Alternative dToF processing schemes

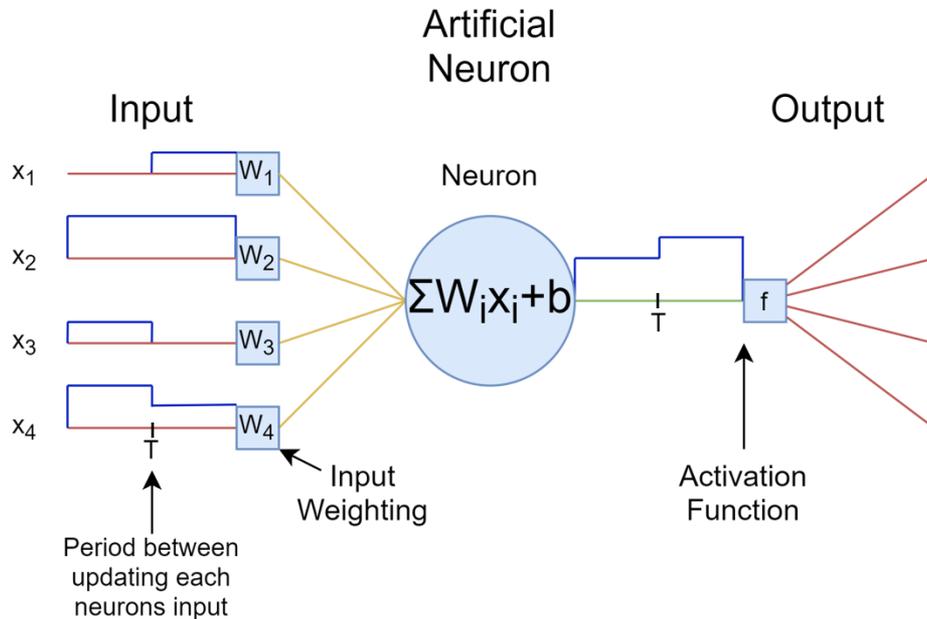
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- Spline-based sketches [Sheehan, IEEE TCI 2024]
- Count-free histograms [Ingle, IEEE TPA 2023]
- Histogram-free processing (averaging) of photon time stamps [Tontini, IEEE Sensors 2024]
- Neural network-based processing [e.g. Milanese, IISW 2023]

**Can we develop a neural-network approach that is TDC-less?**

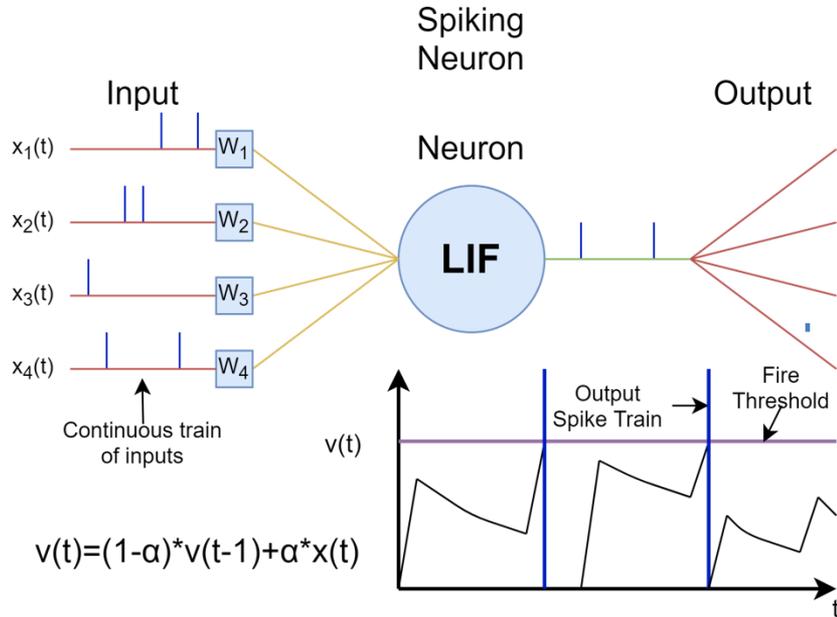
# Traditional artificial neurons

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- Clock driven
- Processes layer by layer
- Represents data as scalars
- Typically applies activation function to the output of the summation

# Spiking neurons



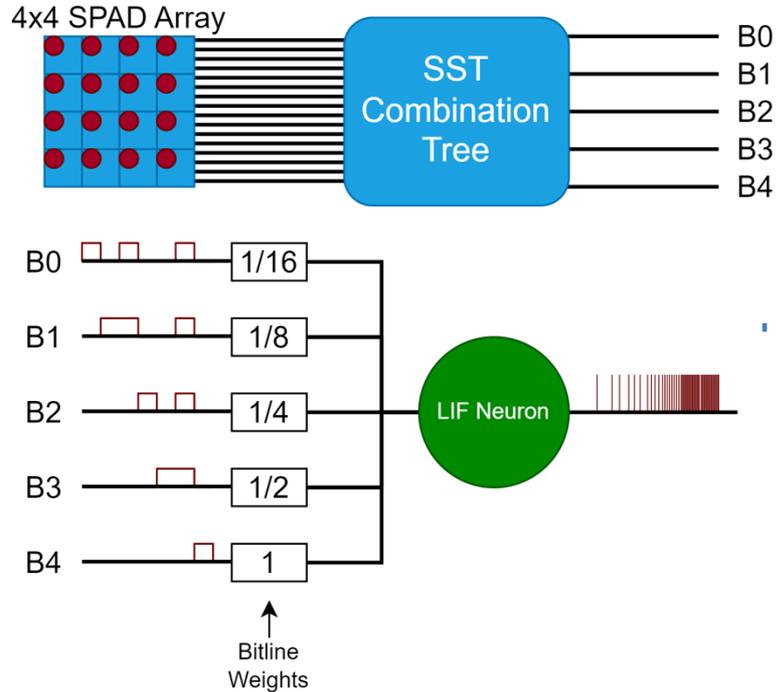
- Asynchronous (though can be clock driven)
- Processes information as the spikes propagate through the network
- Information represented as binary discrete spikes
- Activation function inherent in the neuron dynamics

## SNN vs ANN comparison

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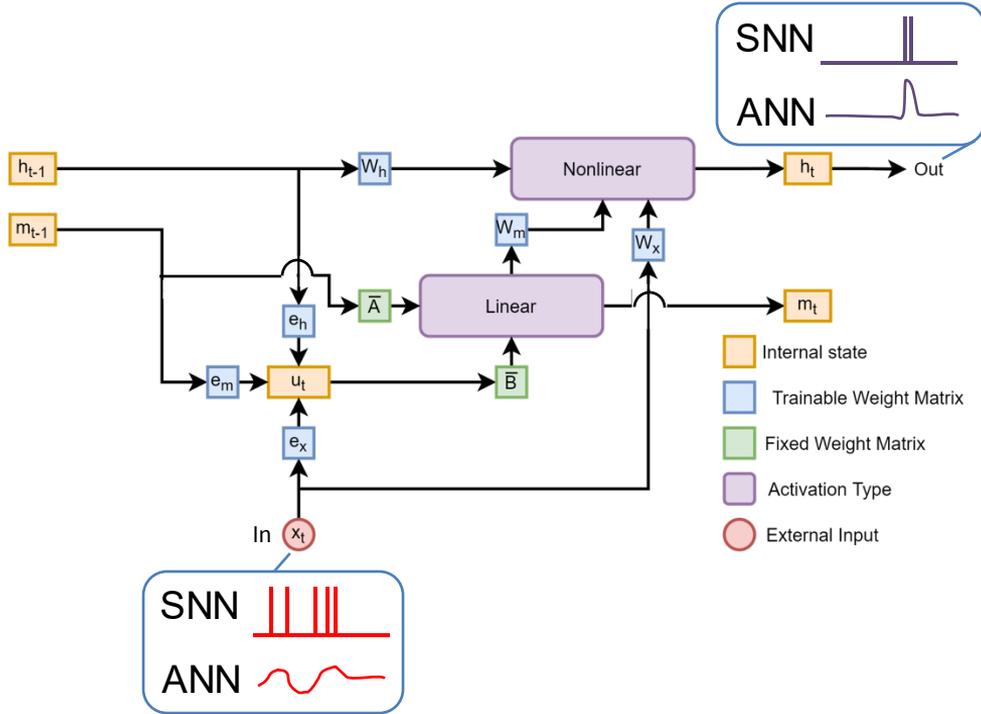
| Potential advantages                                | Disadvantages                                     |
|---|---|
| Fast and parallel information processing            | Difficult to train                                |
| Well suited to processing event/spatiotemporal data | Incompatible with conventional hardware platforms |
| Low energy consumption                              |   |
| Data sparsity                                       |   |

## SPAD events into spikes



- SPAD Events get combined via adder (e.g. [Patanwala, OJSSCS 2022]).
- Each bit line is weighted to increase the membrane potential of the LIF neuron proportional to the value it represents.

# Legendre Memory Unit (LMU) Model



LMU:

- Designed to operate for continuous time operations. i.e.  $\Delta t \rightarrow 0$  and  $T \rightarrow \infty$
- Requires fewer parameters than other recurrent architectures

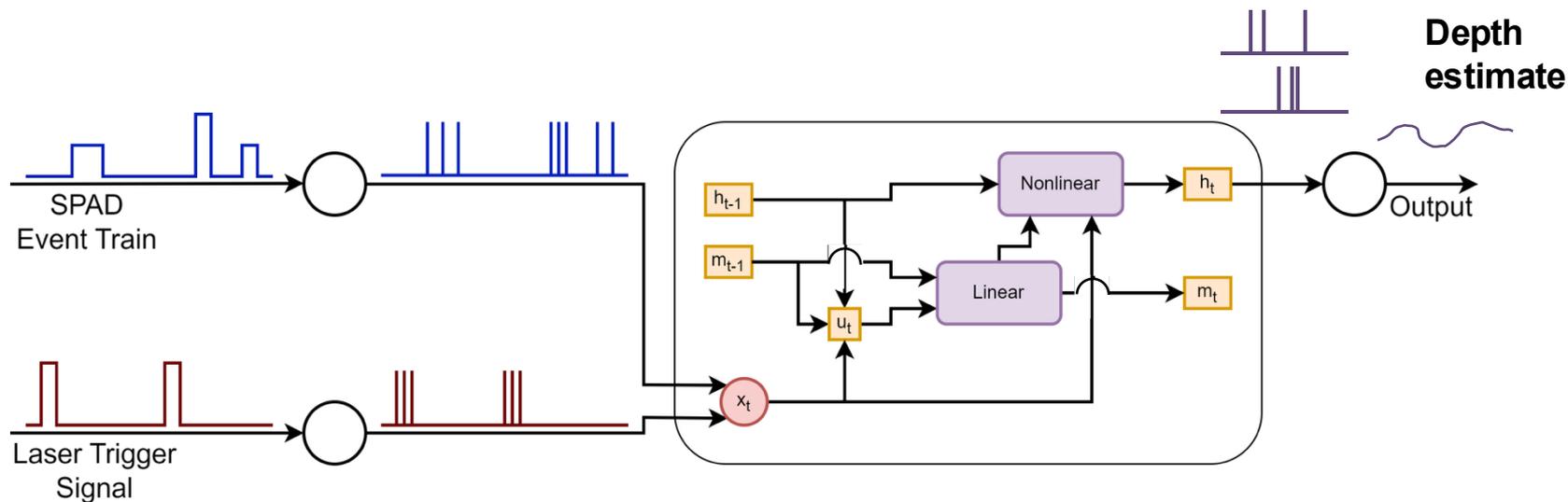
• Governing Equations:

$$U_t = e_x^T X_t + e_h^T H_{t-1} + e_m^T M_{t-1}$$

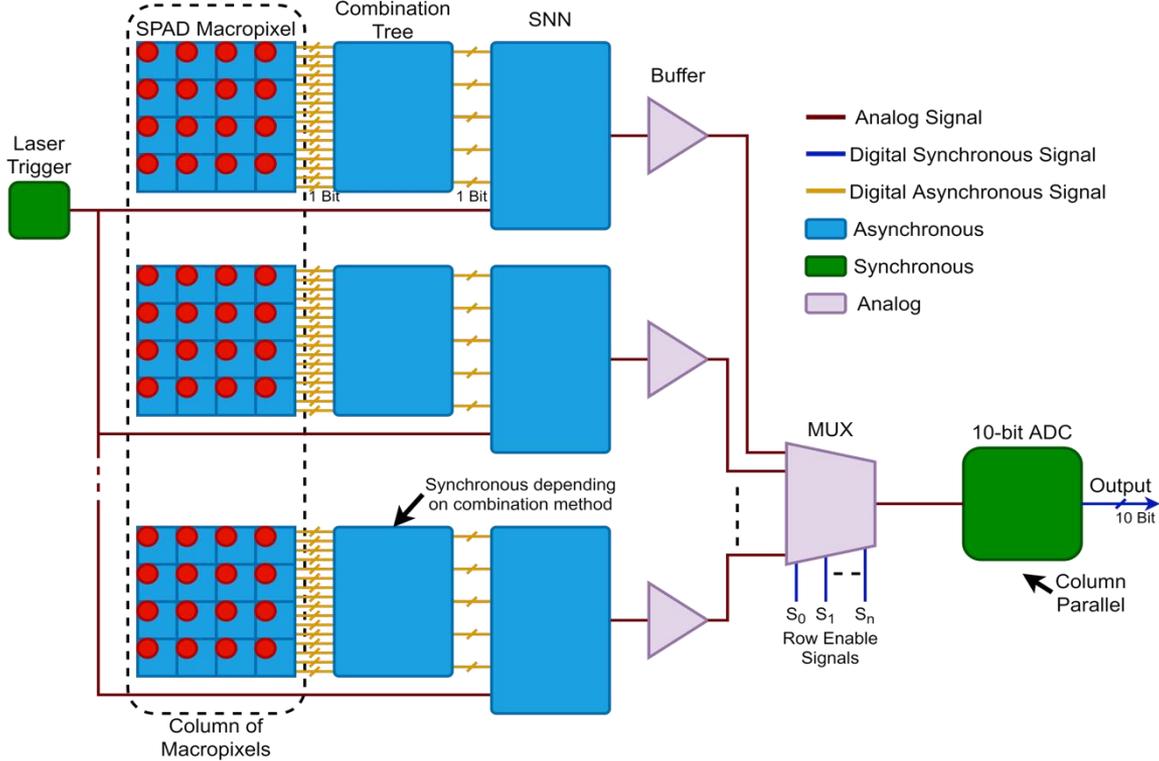
$$M_t = \bar{A} M_{t-1} + \bar{B} U_t$$

$$H_t = f(W_x X_t + W_h H_{t-1} + W_m M_t)$$

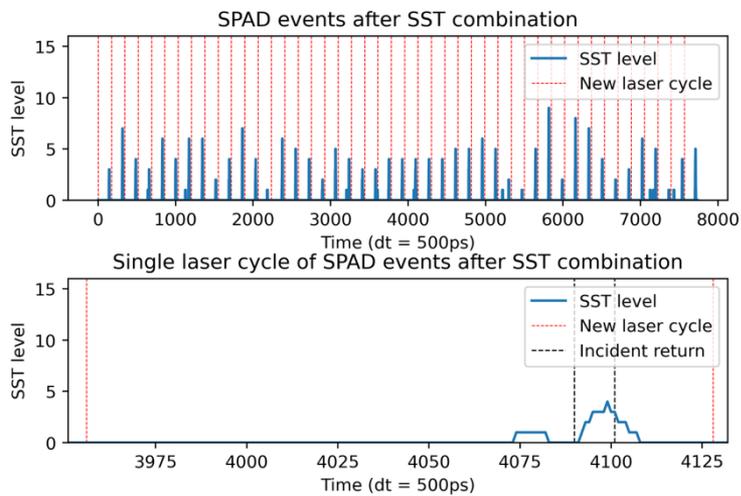
# Overall single (macro)pixel network



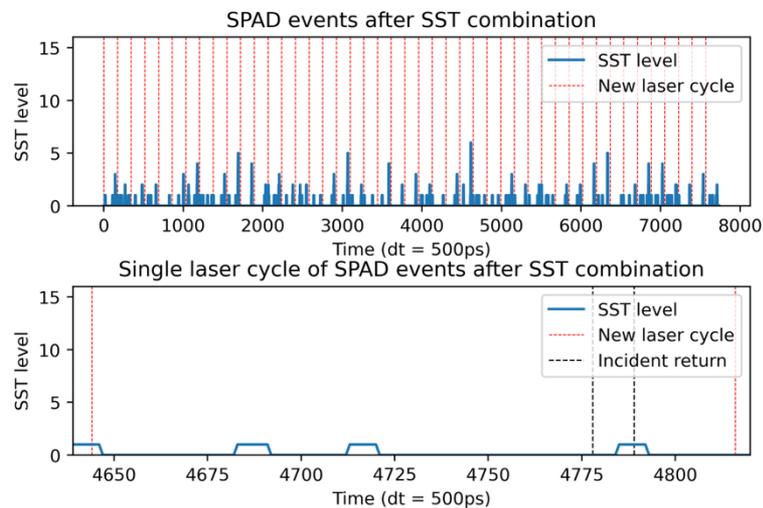
# Proposed image sensor architecture



# Synthetic training data



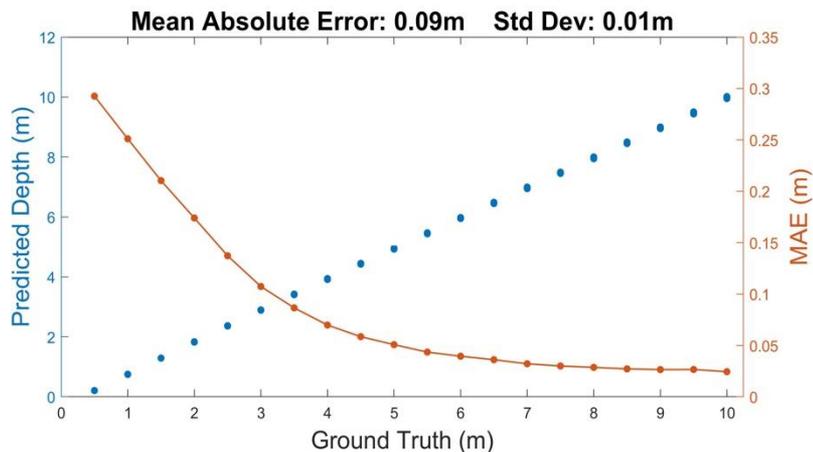
Dist. = 10 m, Reflectivity = 70%, Ambient = 1 klux



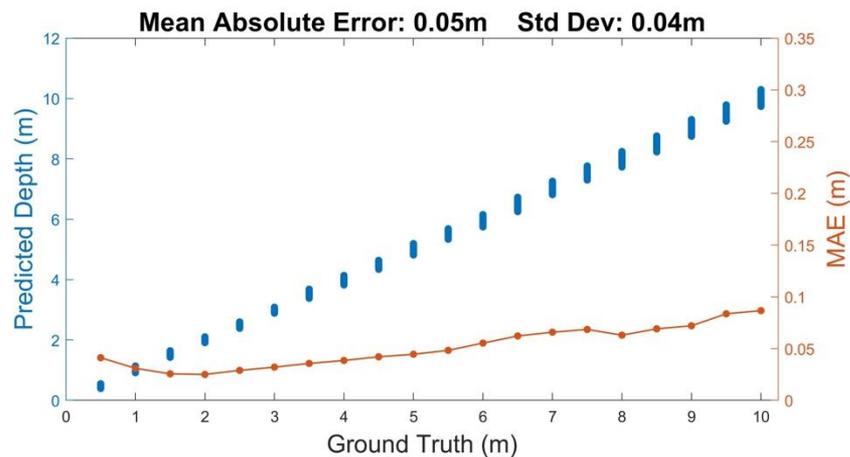
Dist. = 10 m, Reflectivity = 40%, Ambient = 25 klux

# Test results on synthetic data

## Histogram centre-of-mass



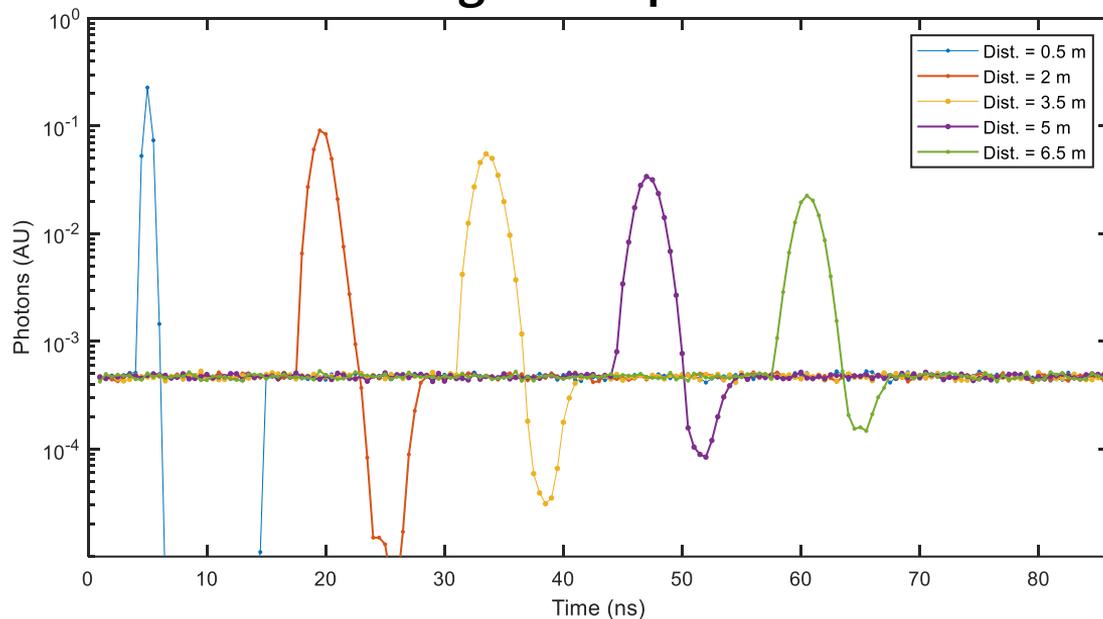
## SNN



Reflectivity = 25%, Ambient = 1 klux

## Test results on synthetic data – pile-up effects

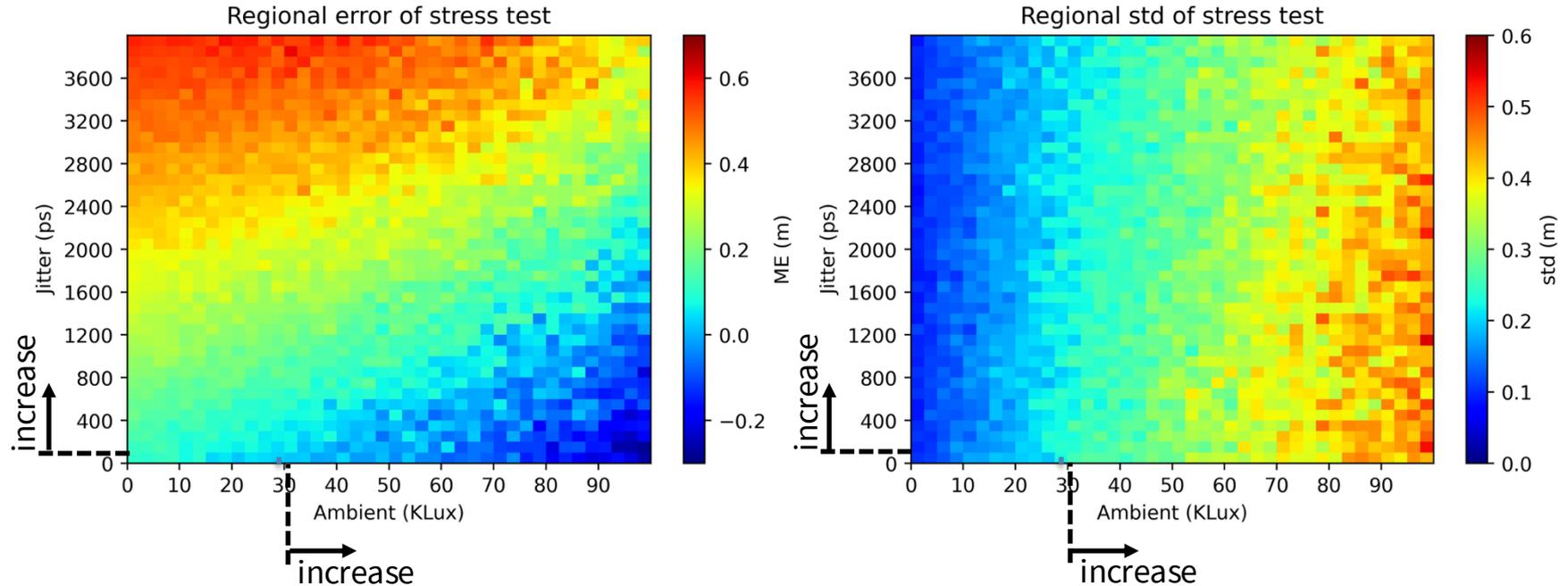
### Histogram of photons



Reflectivity = 70%, Ambient = 25 klux

- Network is learning to recognise SPAD pile-up effects (compression of peak, inhibition of background counts)
- It is correcting for the resulting time skew

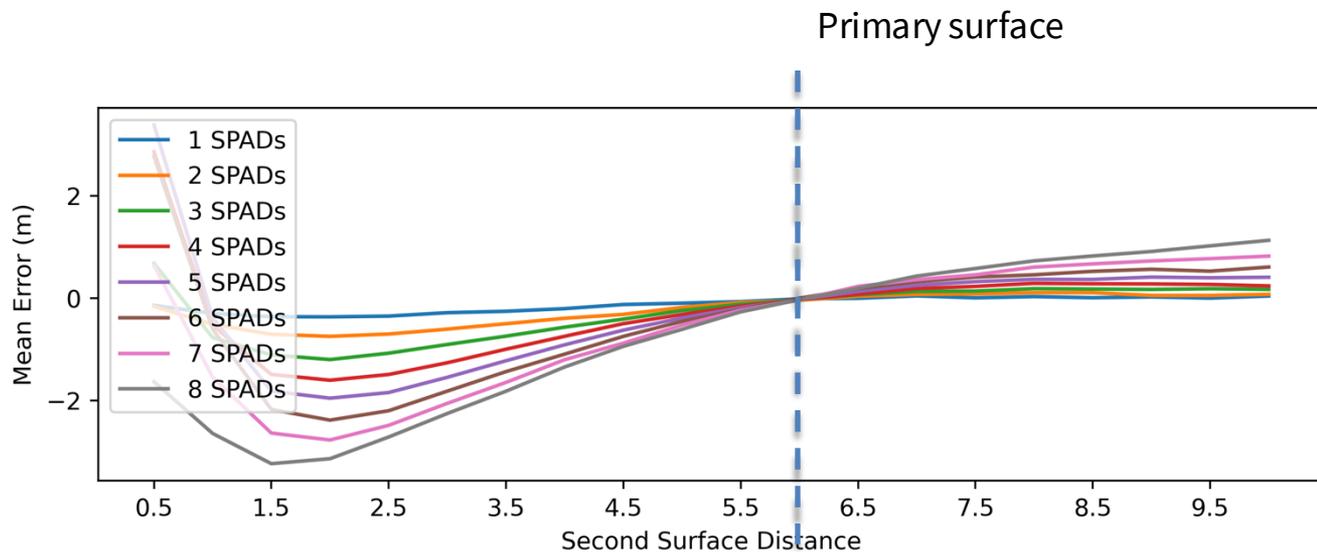
# Test results on synthetic data – stress testing



Reflectivity = 40%, Target distance = 10 m

## Test results on synthetic data - multipeak

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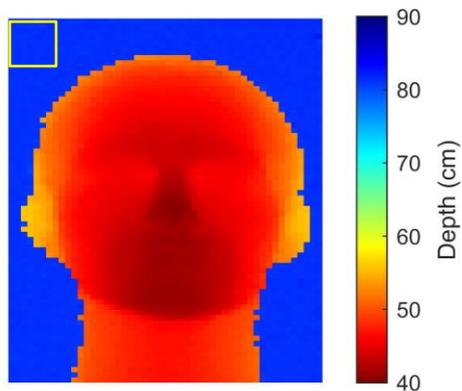


Reflectivity = 40%, Ambient = 25 klux

## Results on real data

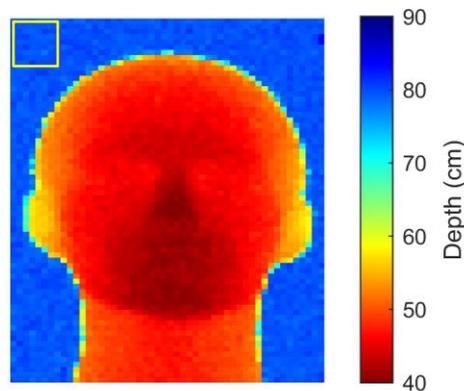
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### Histogram centre-of-mass



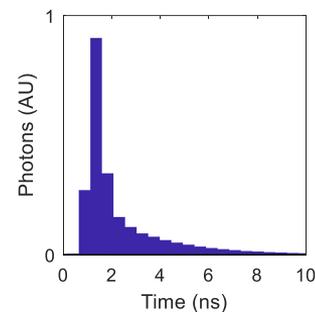
**std = 0.15 cm**

### SNN



**std = 0.59 cm**

### IRF



Mannequin imaged outdoors (data from [Altmann, IEEE TIP 2016])

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## Power and area estimates

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- ~15k neural, ~916k synaptic spikes/exposure
- Analogue circuit implementation of artificial neurons/synapses exist with energy/spike in the fJ range → (SNN only) power consumption in the nW range @30FPS
- Model size: 610 neurons and 3506 synapses
- Compact ( $<0.1\mu\text{m}^2$ ) LIF neurons have been proposed in advanced technology nodes (7nm FinFET) with high (1GHz) firing rates
- In the future the model may fit under a  $40\times 40\mu\text{m}$  SPAD macropixel.

## Conclusions

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- SNN processing of SPAD dToF data was demonstrated
- Low latency (depth estimate is available at the end of exposure time)
- Low precision but good accuracy compared with conventional processing, and reasonable robustness to conditions beyond the training dataset
- Potential for low power implementation. May suit applications such as a low power object detection for robots or drones.

# Acknowledgements

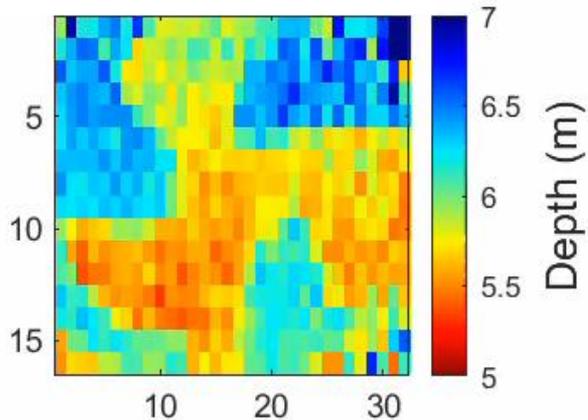
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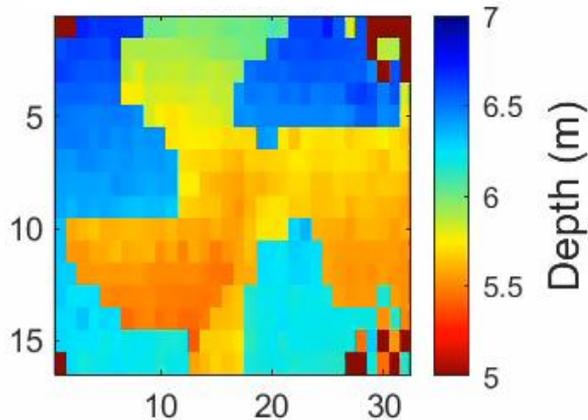
## Results on real data (cont.)

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SNN



Histogram centre-of-mass



SBR  $\approx$  2

IRF

