FLOW FROM A FISH'S PERSPECTIVE: HOW LIVE FISH, BIOINSPIRED SENSORS AND AI CAN BE USED TO IMPROVE FISH PASSAGE

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Fish Counters

US Bonneville Dam (1938)

https://www.nwp.usace.army.mil/Media/Images/igphoto/2000754585/

HydroCam (2020)

https://iamhydro.com/de/ausruestung/hydro-camerasystem.php

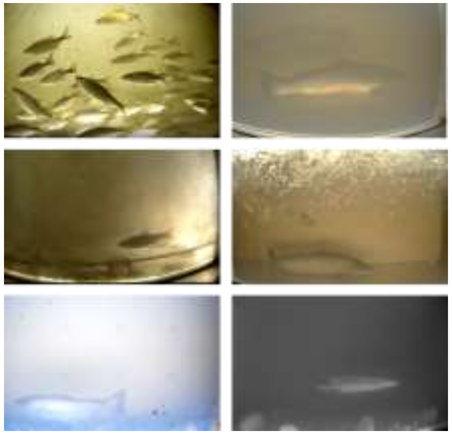
Smart Fish Counter AI

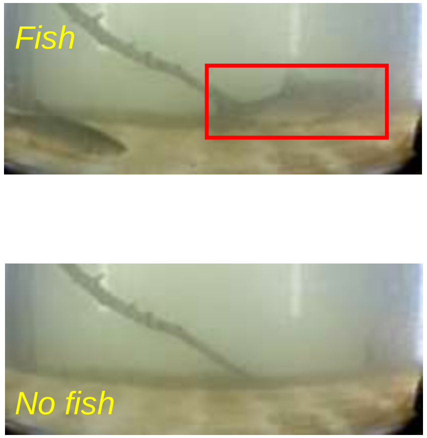
Upload videos from fish counter

Classification of the six environmental conditions

Sort and classify videos with fish and no fish

Classification of fish species, size and migration behaviour



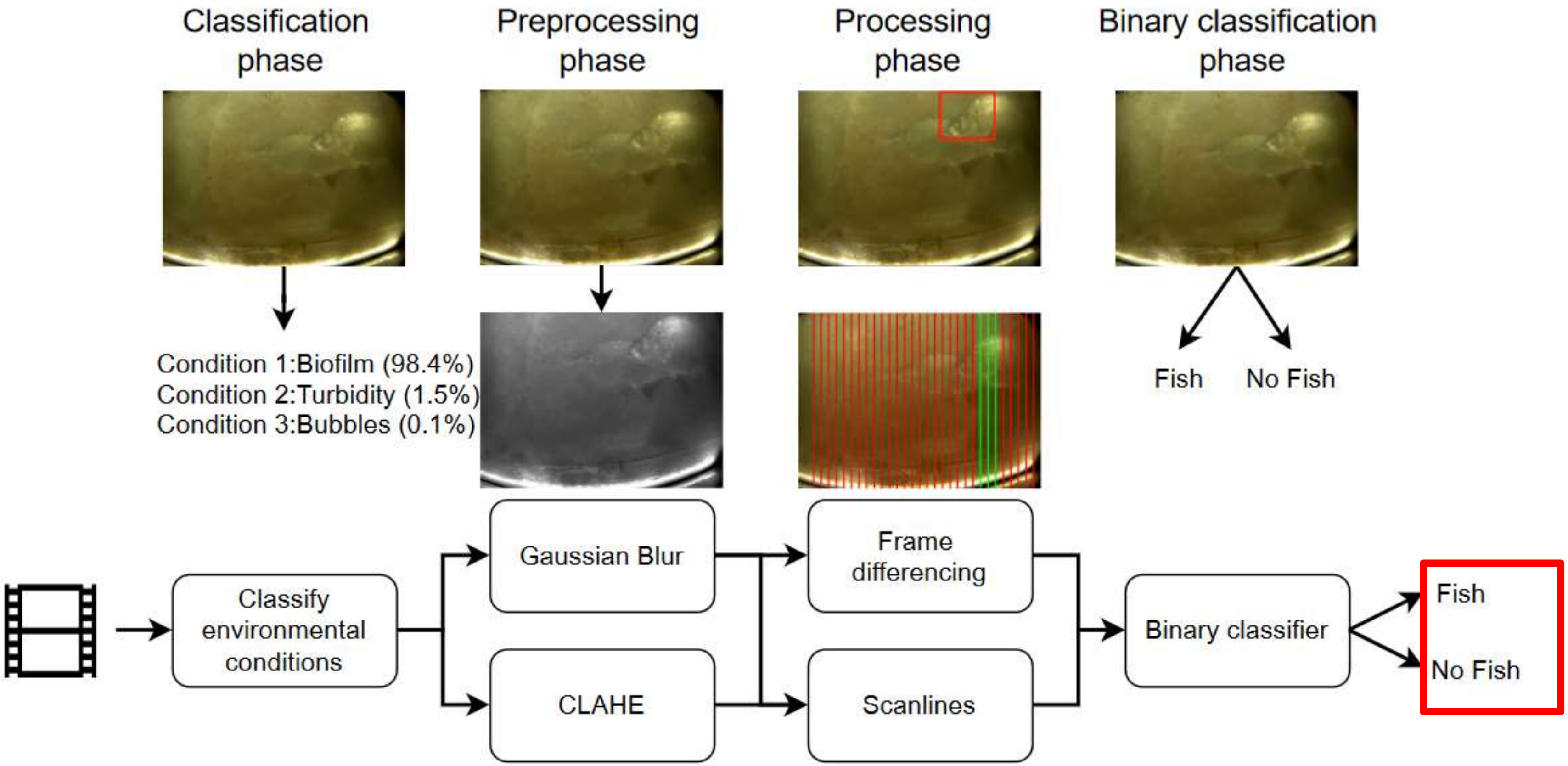


Chub (96.1%)

Length (45 ± 3.7 cm)
Behaviour: *Up-In*

Mockenhaupt, B.; Tuhtan, J.A. (2023). **BfG-Projekt Smart Fish Counter: Automatisierte Bewertung von Art, Größe und Migrationsverhalten durch Künstliche Intelligenz.** *Wasserwirtschaft* (2-3)

Where are the fish and what are they doing?



Classification phase

Preprocessing phase

Processing phase

Binary classification phase

Condition 1:Biofilm (98.4%)
Condition 2:Turbidity (1.5%)
Condition 3:Bubbles (0.1%)

Fish

No Fish

Classify environmental conditions

Gaussian Blur

CLAHE

Frame differencing

Scanlines

Binary classifier

Fish

No Fish

Soom, J.; Pattanaik, V.; Mairo, M.; Tuhtan, J.A. (2022). **Environmentally adaptive fish or no-fish classification for river video fish counters using high-performance desktop and embedded hardware.** *Ecological Informatics* (72)

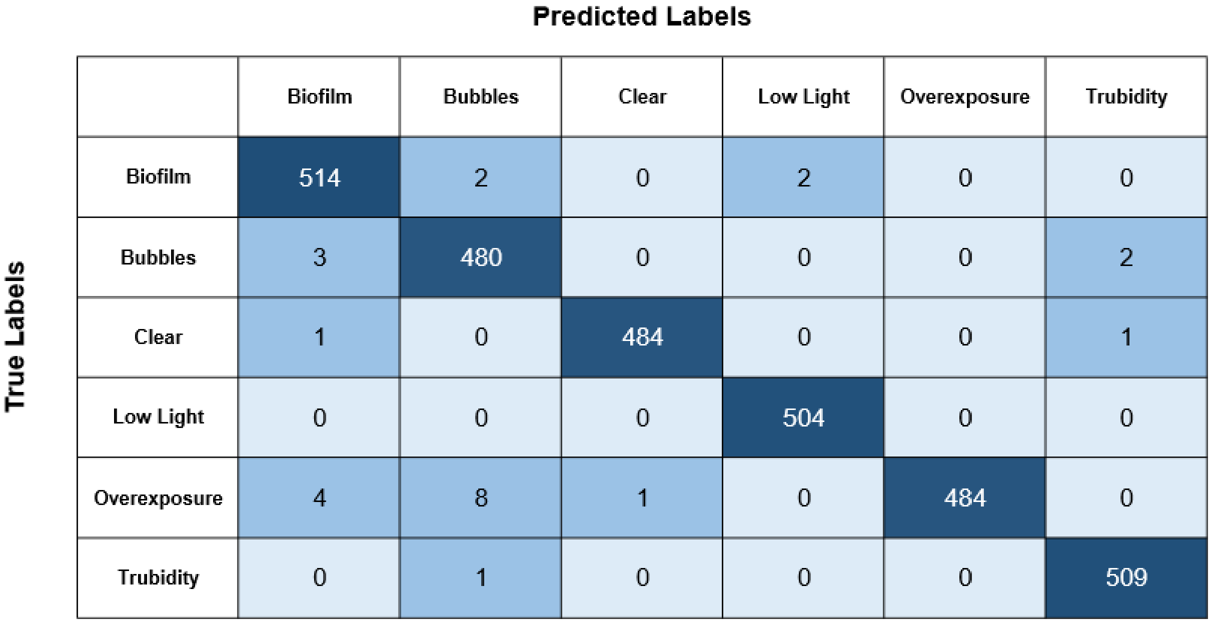
Clear vs. Biofilm

Overexposure & Bubbles vs. Low Light

Turbidity (the worst of all...)

CNN for classification

Environmental Conditions



Predicted Labels

True Labels

	Biofilm	Bubbles	Clear	Low Light	Overexposure	Trubidity
Biofilm	514	2	0	2	0	0
Bubbles	3	480	0	0	0	2
Clear	1	0	484	0	0	1
Low Light	0	0	0	504	0	0
Overexposure	4	8	1	0	484	0
Trubidity	0	1	0	0	0	509

Fish / No-Fish

3000 Videos

(150-900 Images / Video)

6 Classes

250 Video with,

250 Video without Fish

Mean Accuracty: 88.5%

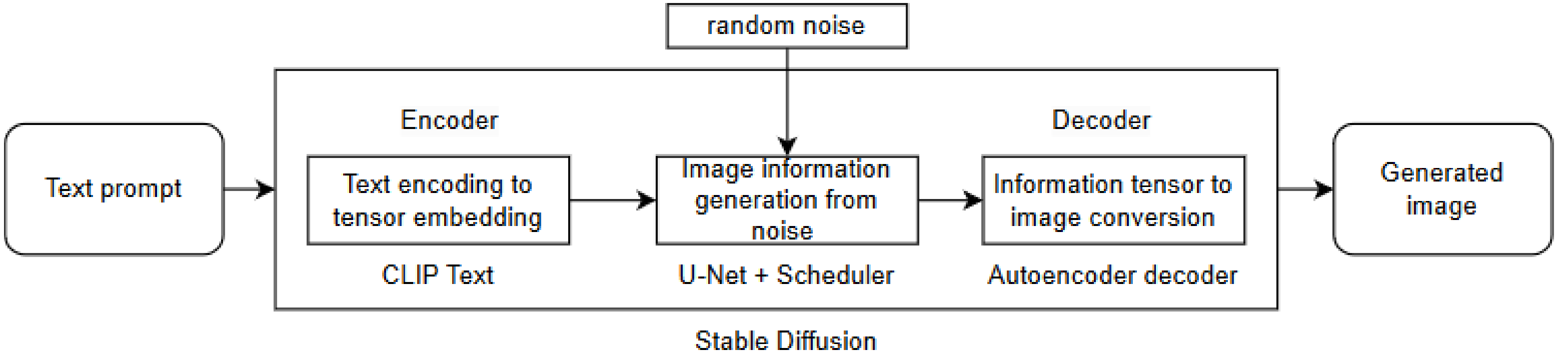
F1 Score: 0.88

TP: 44% FP: 6%

TN: 43% FN: 7%

Soom, J.; Pattanaik, V.; Mairo, M.; Tuhtan, J.A. (2022). **Environmentally adaptive fish or no-fish classification for river video fish counters using high-performance desktop and embedded hardware.** *Ecological Informatics* (72)

Synthetic Fish



random noise

Text prompt

Encoder

Text encoding to tensor embedding

CLIP Text

Image information generation from noise

U-Net + Scheduler

Decoder

Information tensor to image conversion

Autoencoder decoder

Stable Diffusion

Generated image

Synthetic

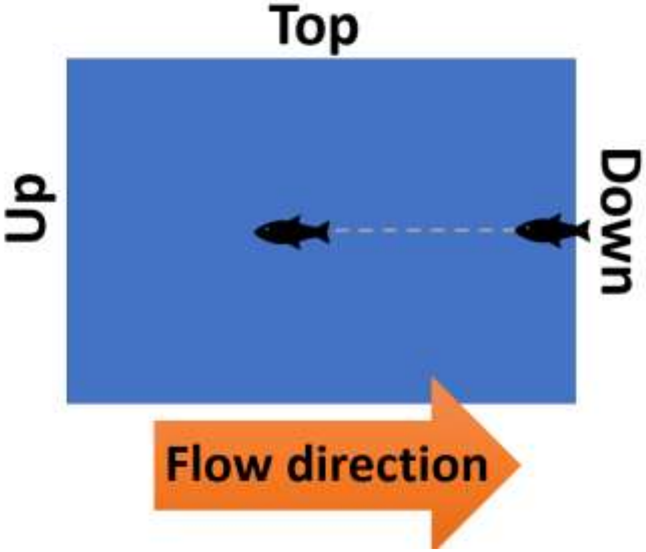
Real

Dubrovinskaya, E.; Tuhtan, J.A. (2023) **This Fish Does not Exist: Fish Species Image Augmentation using Stable Diffusion.** *IEEE Oceans Conference (Dublin)*

The Good, the Bad and the Ugly

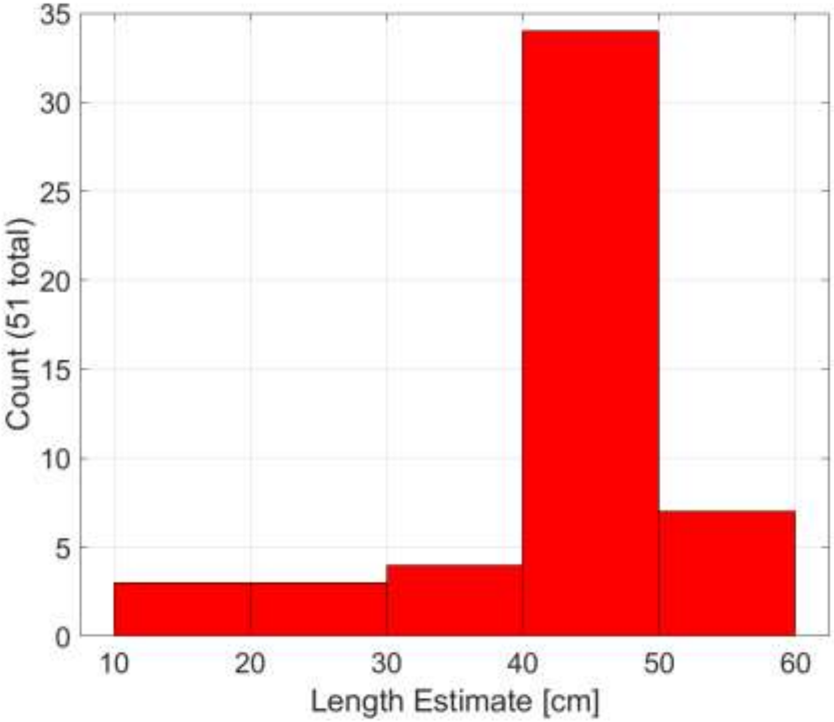
Dubrovinskaya, E.; Tuhtan, J.A. (2023) **This Fish Does not Exist: Fish Species Image Augmentation using Stable Diffusion.** *IEEE Oceans Conference (Dublin)*

Species, behaviour and size



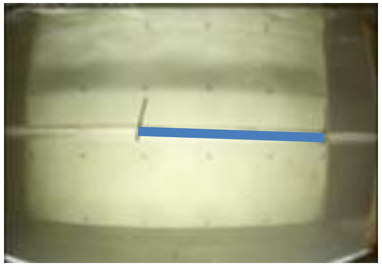
Behaviour „UP-IN“

Size is actually the most difficult!



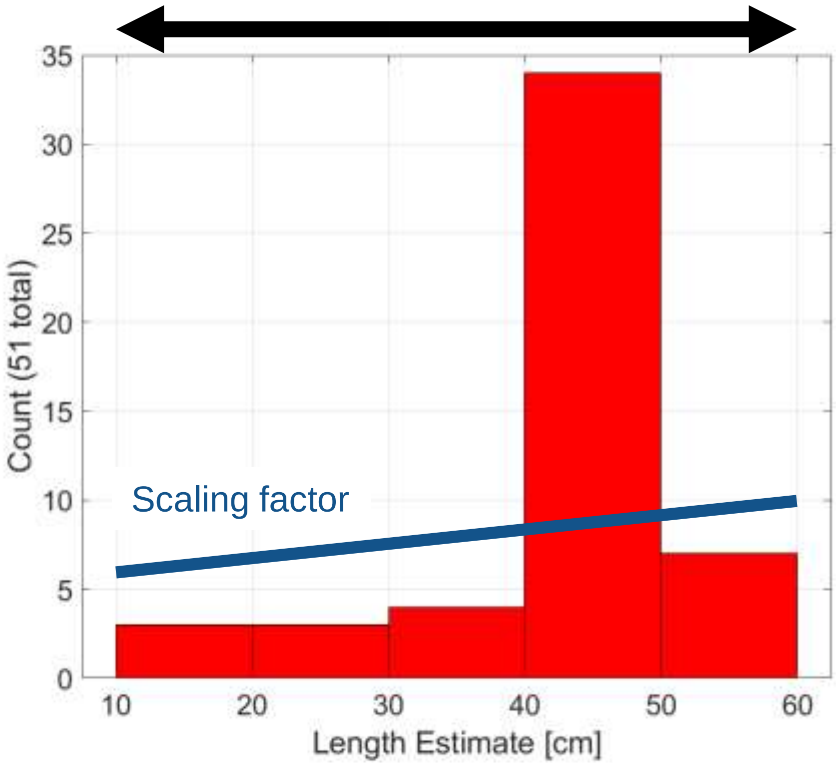
Dynamic scaling factor needed

Front
10 px / cm



Middle
8 px / cm

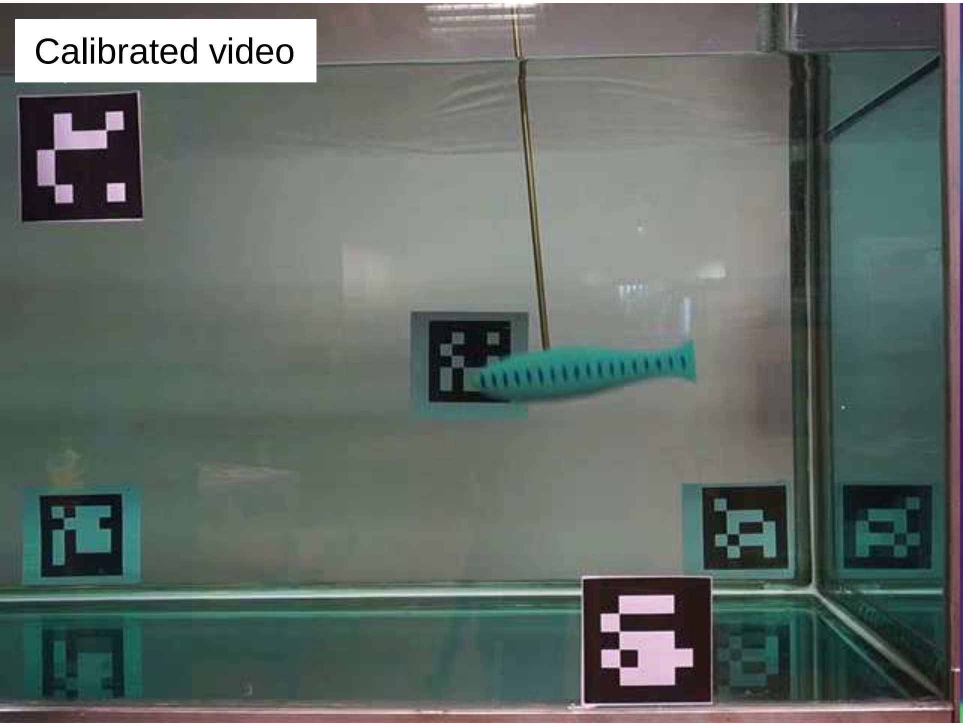
Back
6 px / cm



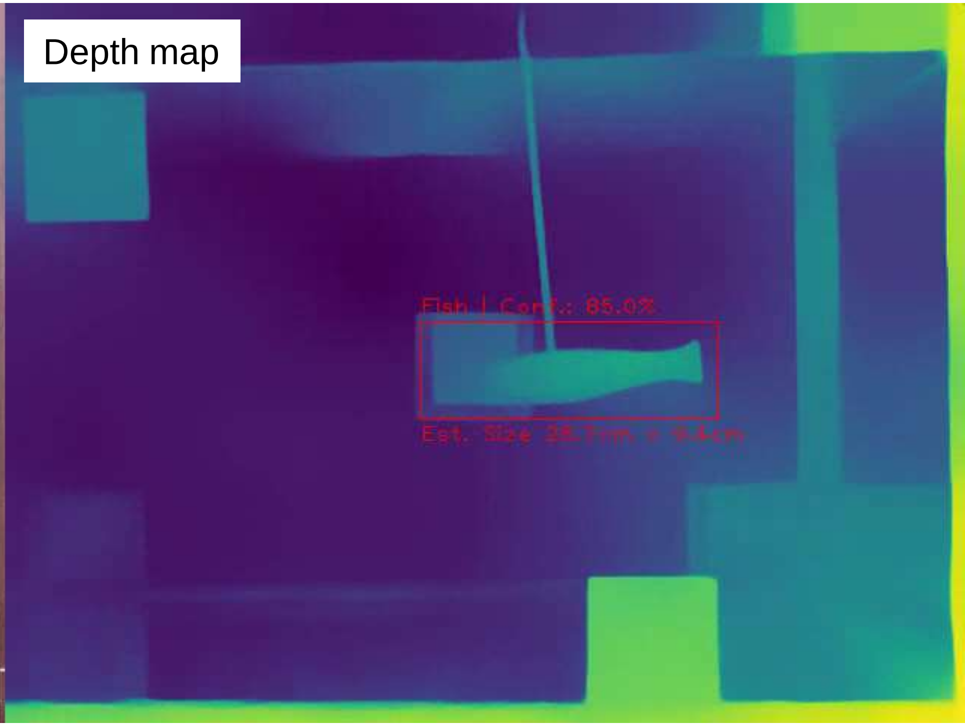
Fish near the back

Fish near the front

Depth mapping using ML



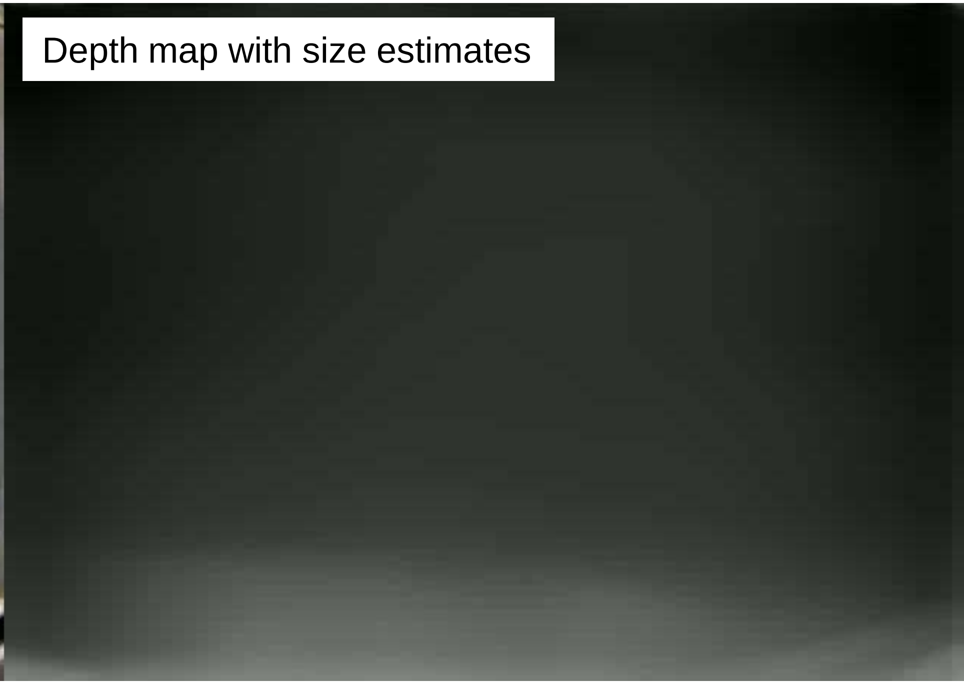
Calibrated video



Depth map

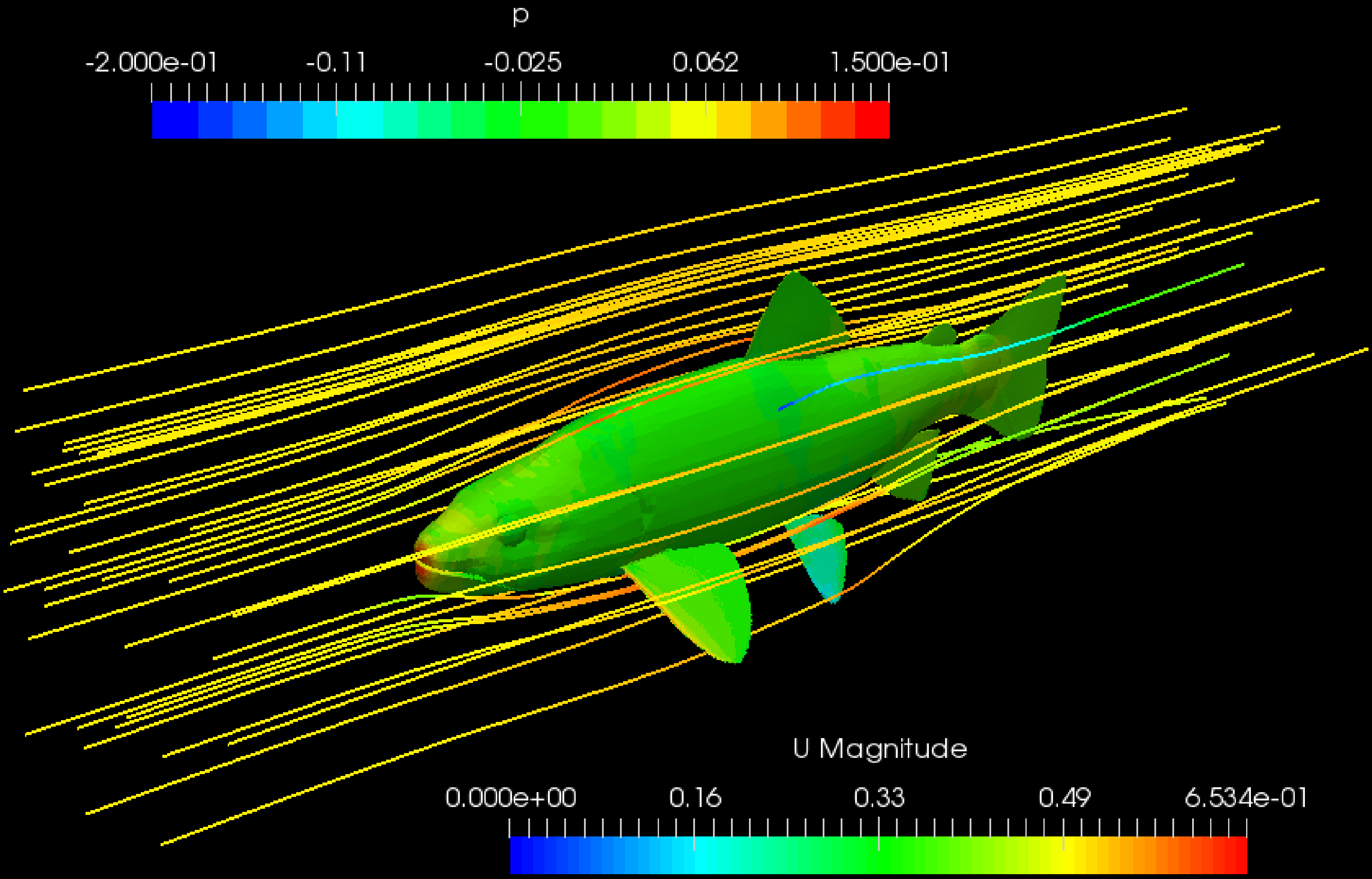
Depth mapping in River Watcher

Uncalibrated video

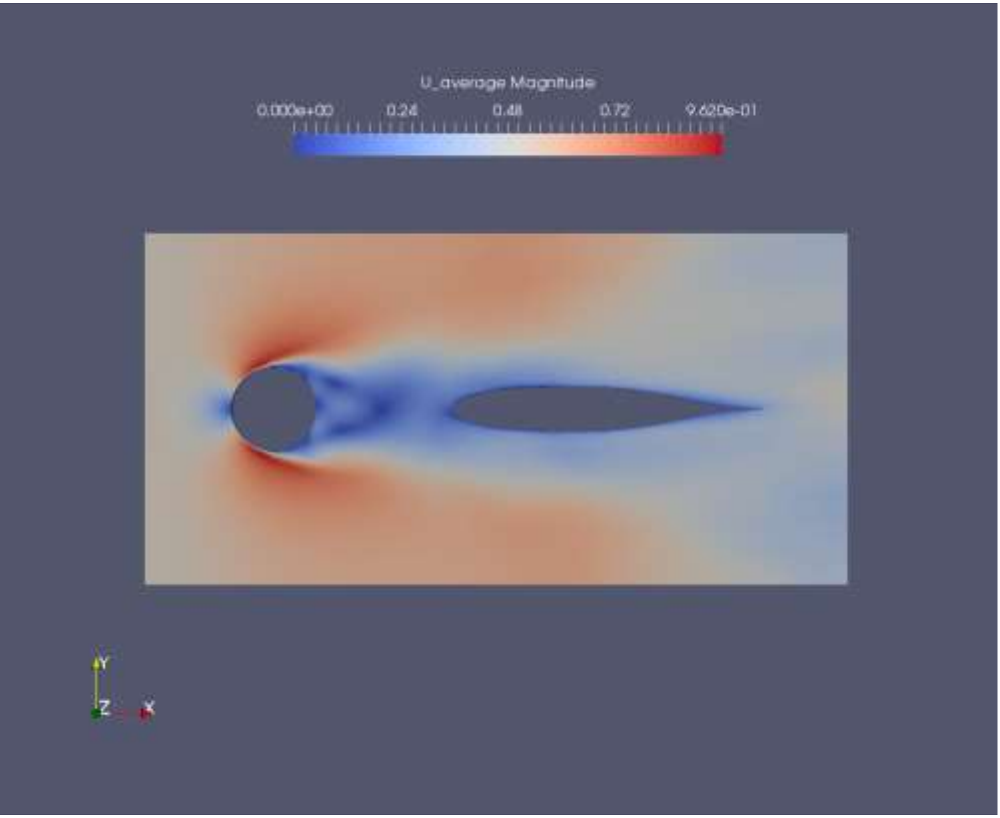


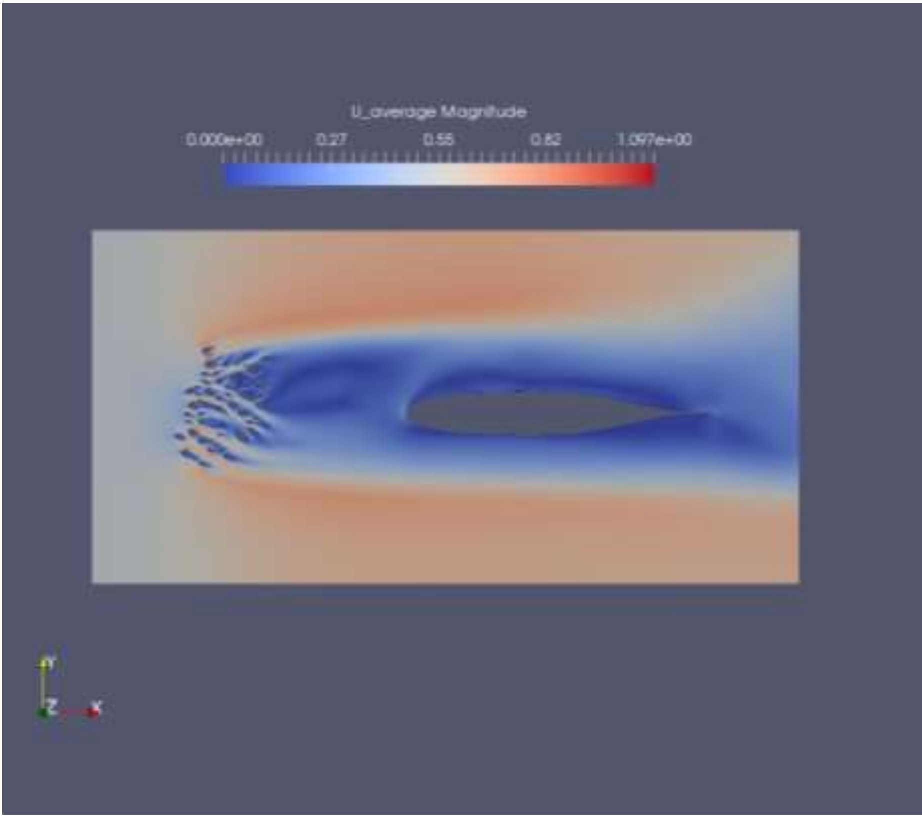
Depth map with size estimates

A fish is not a point in **space**

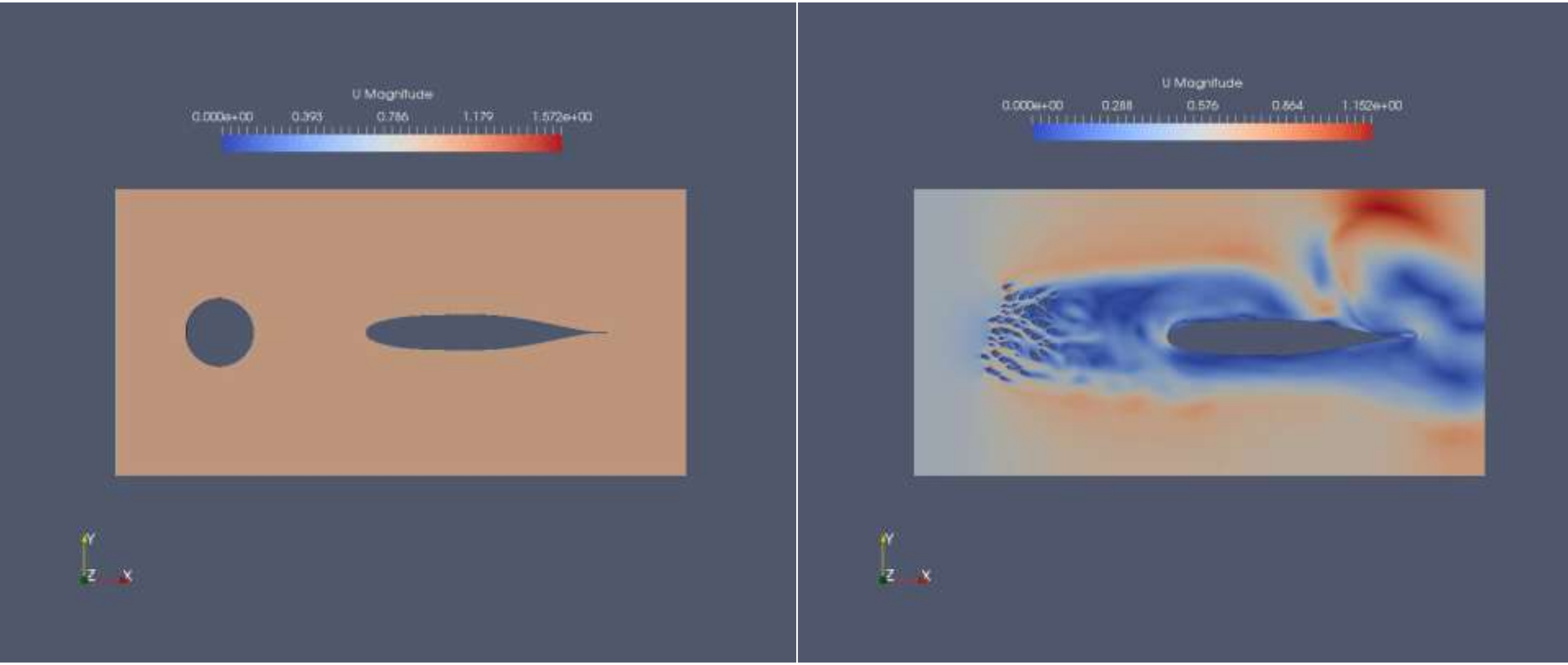


A fish is not a point in **time**





Changing flow = changing interaction



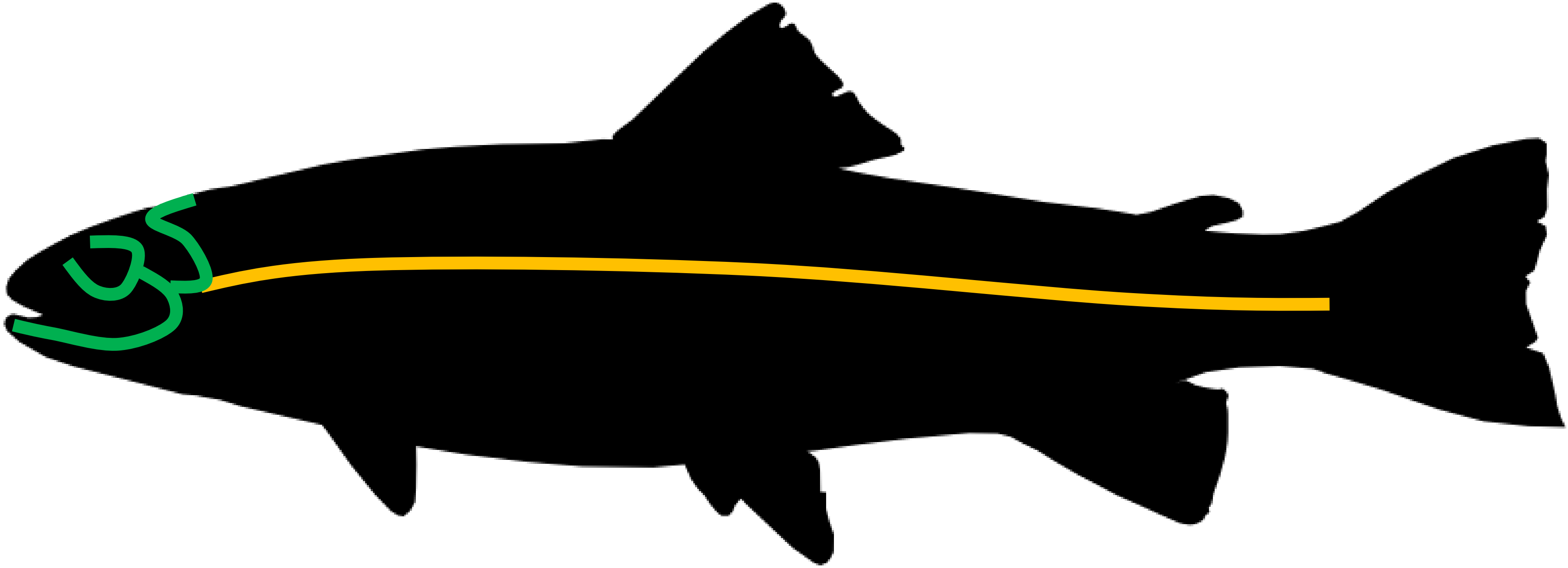
Large eddy simulations of 2D flow around a fish-shaped body

The Lateral Line

Fish use their **lateral line** primarily to sense the **local flow**

Pollach *(Pollachius virens)*

Superficial and Canal Neuromasts



Superficial Neuromasts < 30 Hz

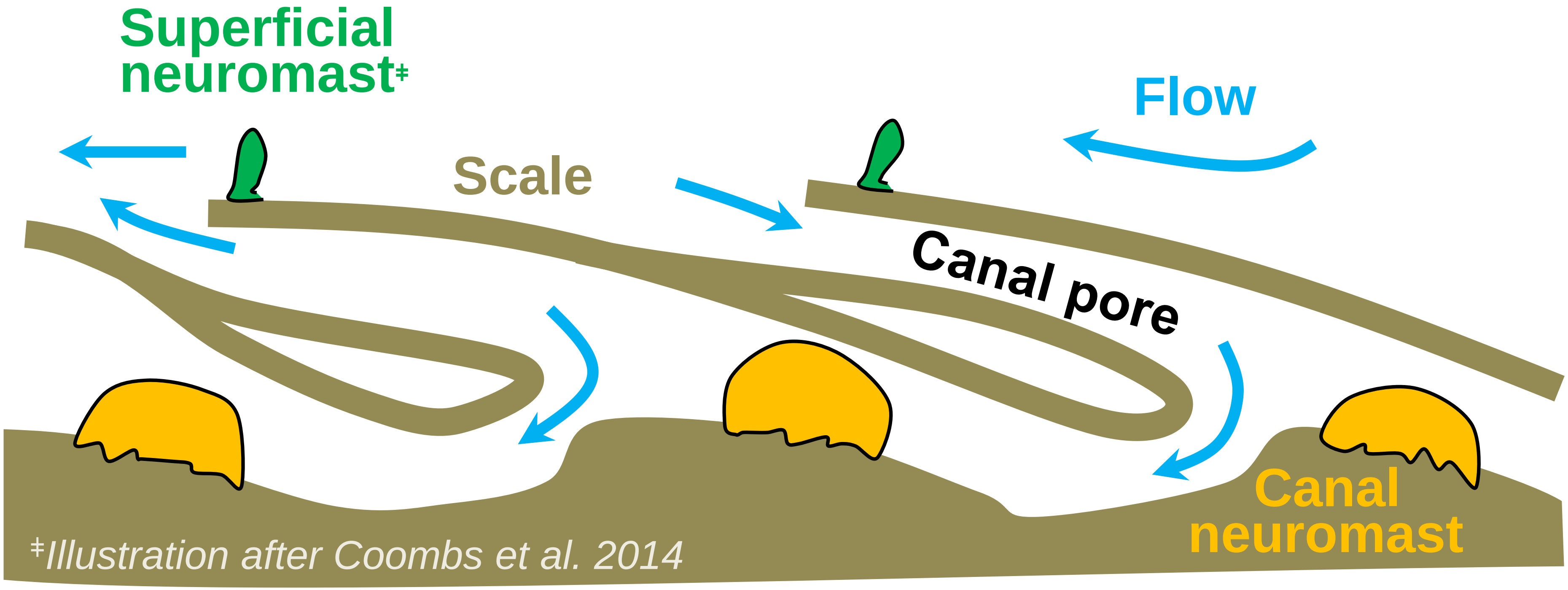
Canal Neuromasts 30-200 Hz

Superficial and Canal Neuromasts

Fish use **two modalities** to sense acceleration and **gradients**

Superficial – senses velocity gradient at point

Canal – senses pressure gradient over body



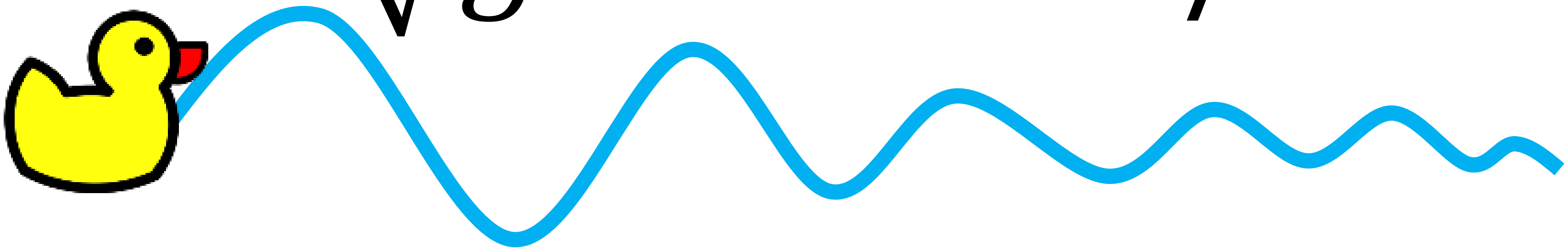
‡*Illustration after Coombs et al. 2014*

Ristolainen, A.; Tuhtan, J. A.; Kuusik, A.; Kruusmaa, M. (2016). **Hydromast: A Bioinspired Flow Sensor with Accelerometers.** *Biomimetic and Biohybrid Systems* (510−517)

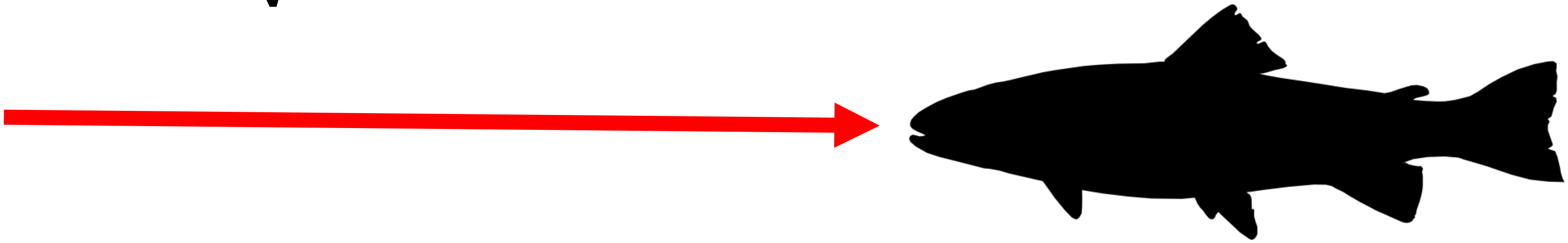
Origins of flow information

Water waves are **slow**, and sound waves are **fast**

$$\sqrt{gd} \approx 10\,m/s$$



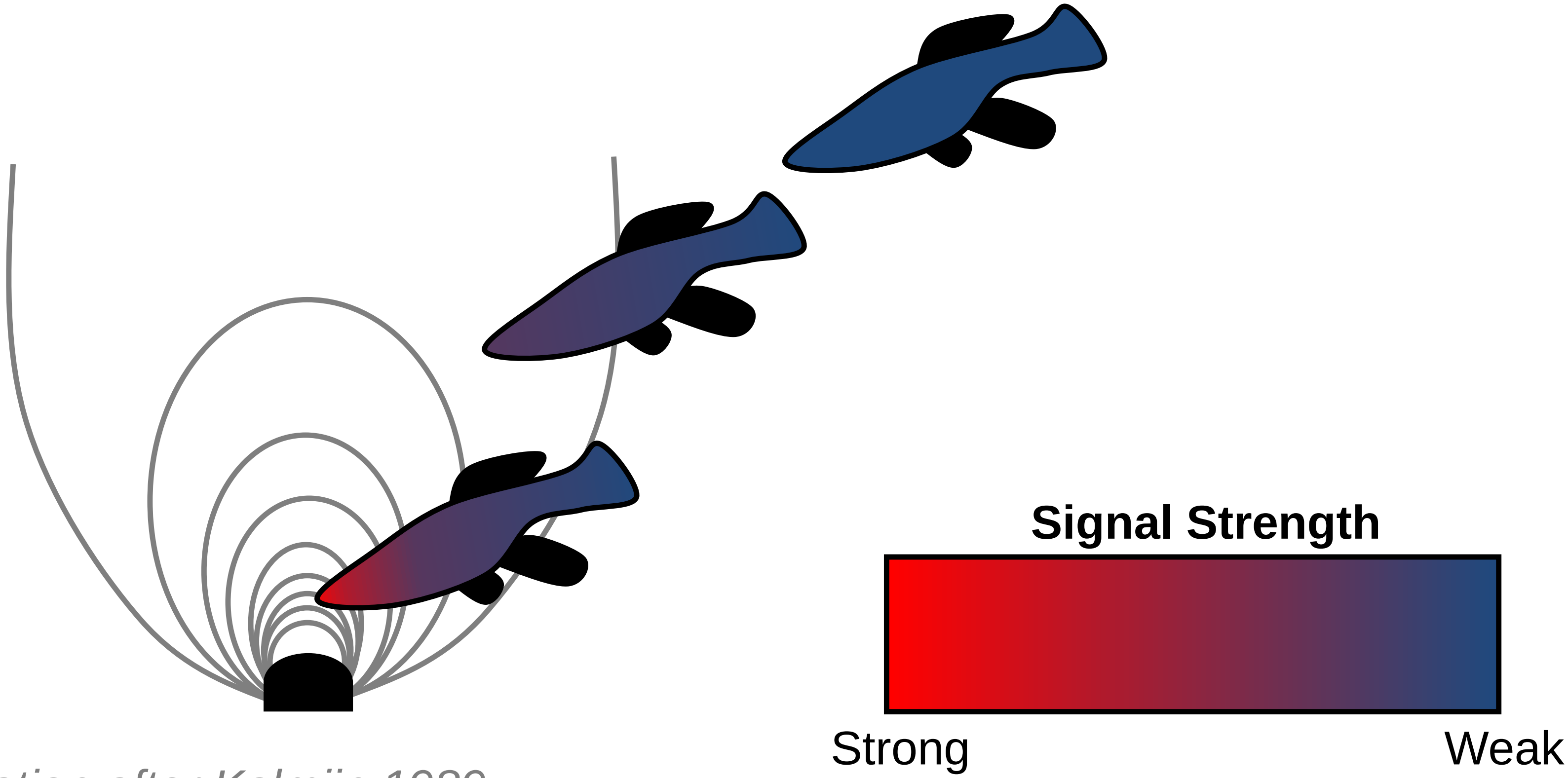
$$\sqrt{E/\rho} \approx 1500\,m/s$$



The Octavolateralis afferent system

Hydrodynamic detection of **vibrational signals**[‡], including sound

Consists of the **inner ear**, **superficial** and **canal neuromasts**

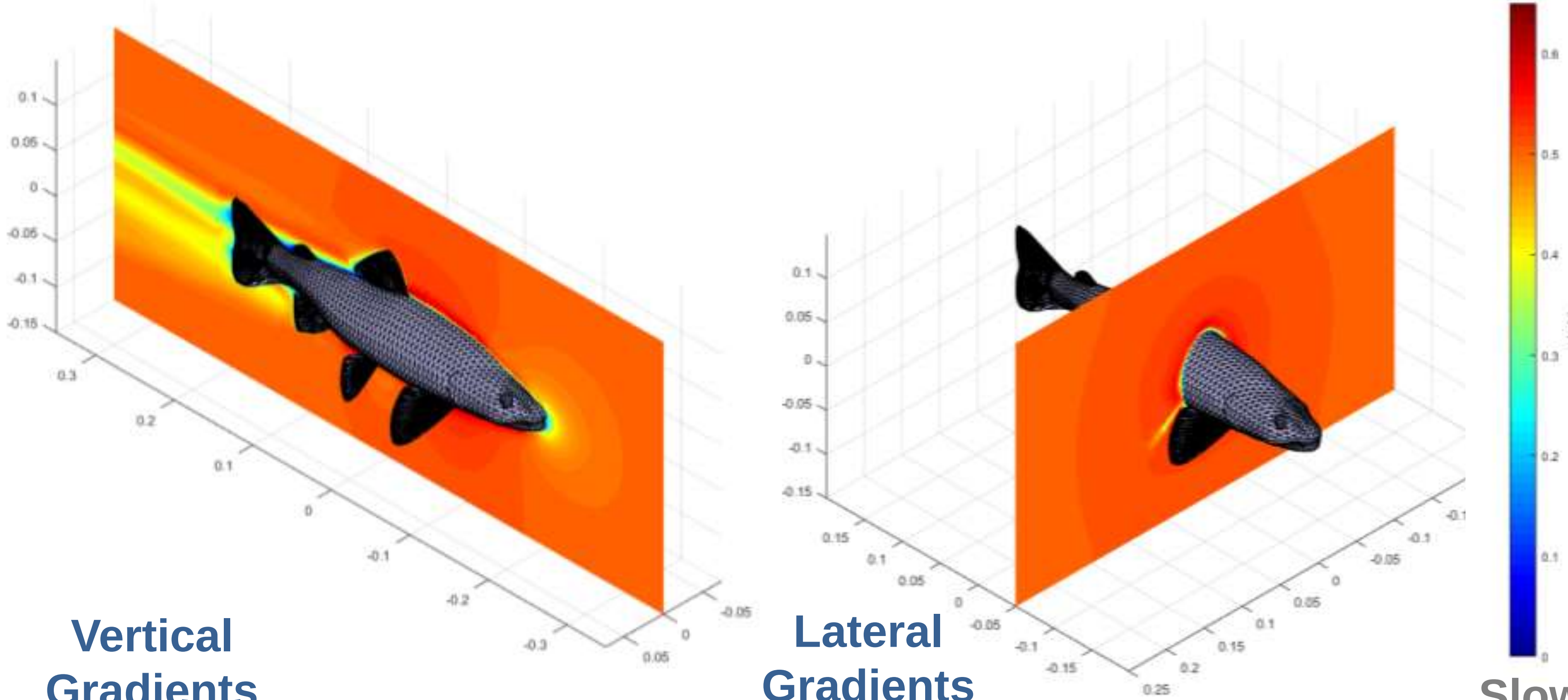


[‡] *Illustration after Kalmijn 1989*

Flow Gradients

Flow around a fish is distributed into fast and slow regions

The **change** of flow is the **flow gradient**



Fast

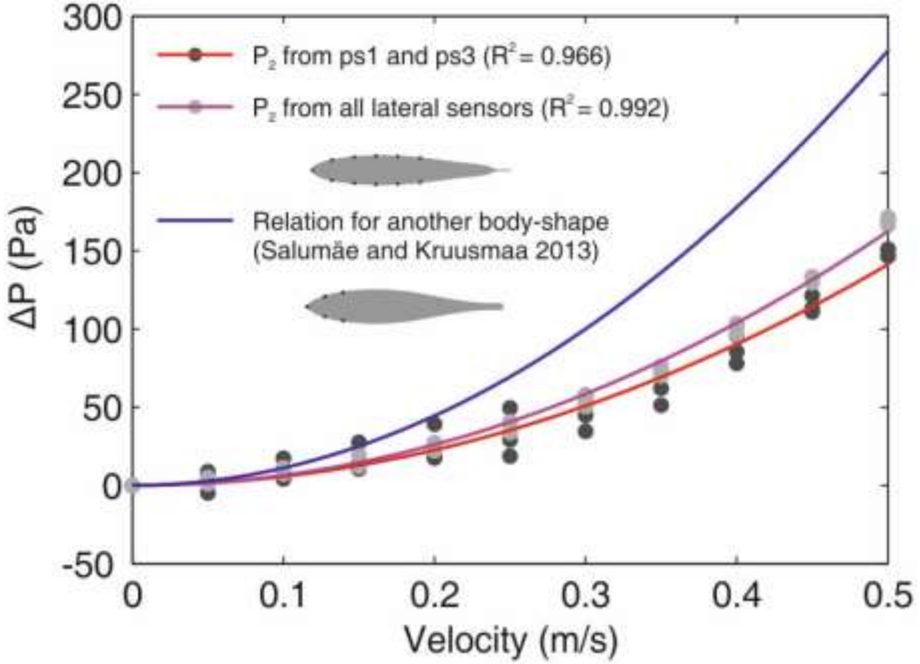
Slow

Vertical Gradients

Lateral Gradients

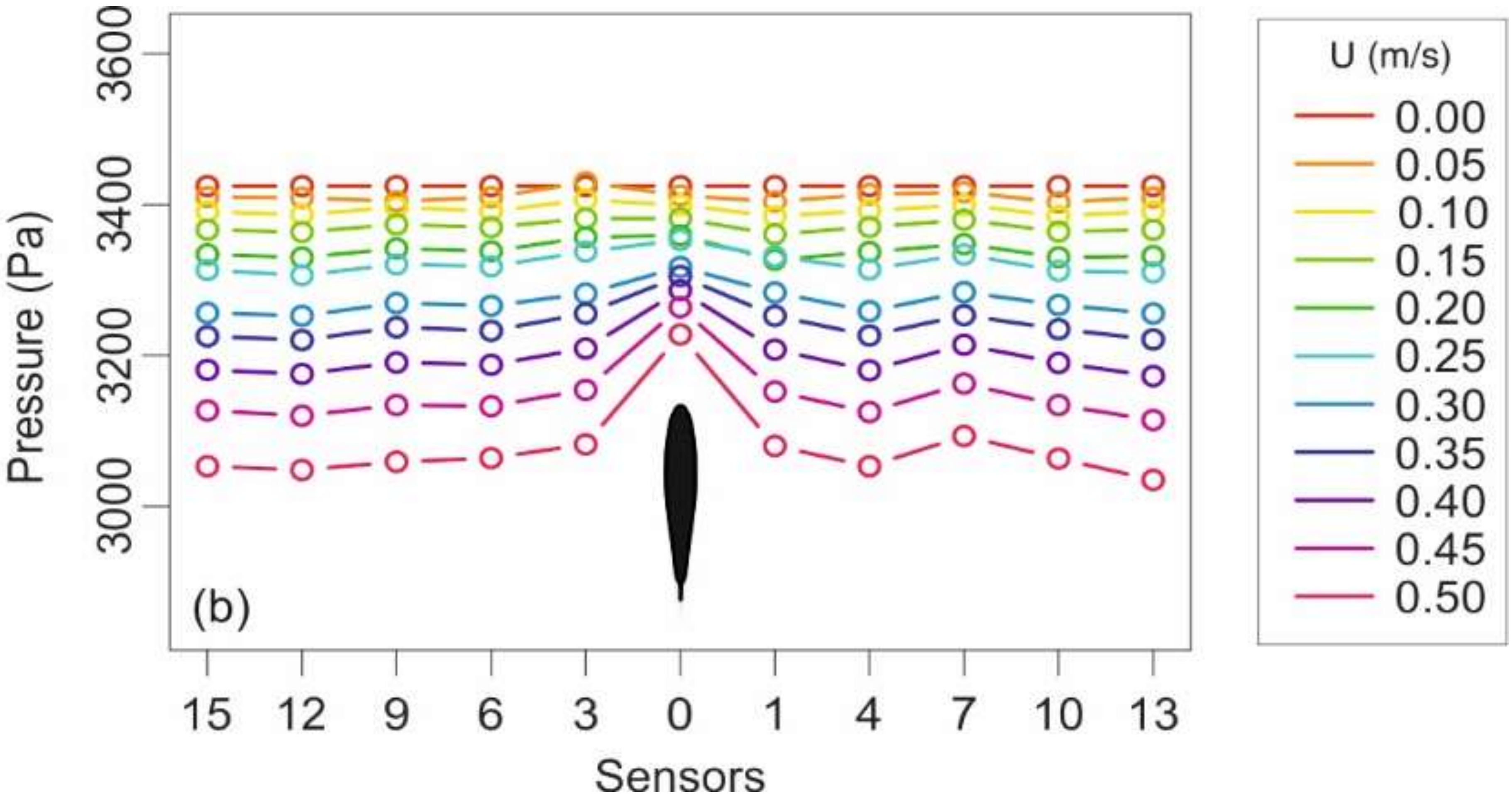
Using fluid-body interactions

The **flow gradients** depend on the body and the flow field



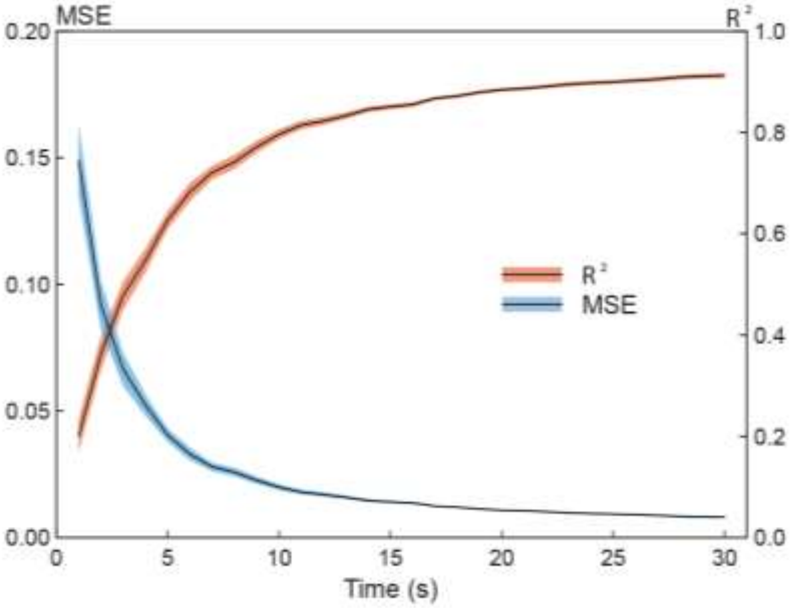
Fuentes-Pérez, J. F.; Tuhtan, J. A; Carbonell-Baeza, R.; Musall, M.; Toming, G.; Muhammad, N.; Kruusmaa, M. (2015). **Current velocity estimation using a lateral line probe**. *Ecological Engineering*, 85, 296−300, 10.1016/j.ecoleng.2015.10.008.

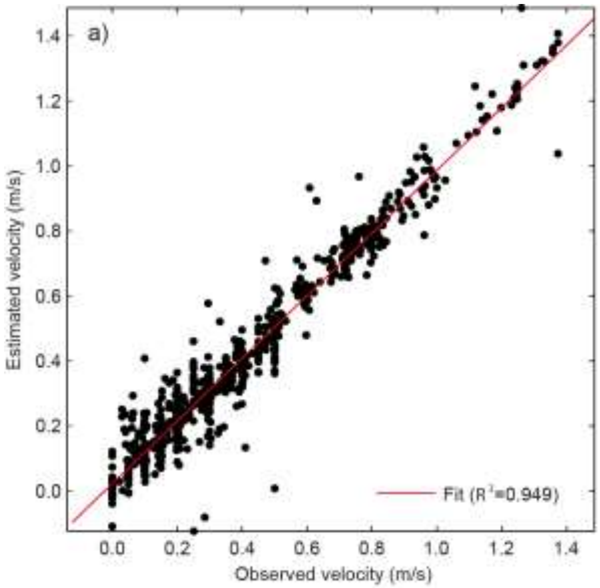
Gradients map pressure to velocity

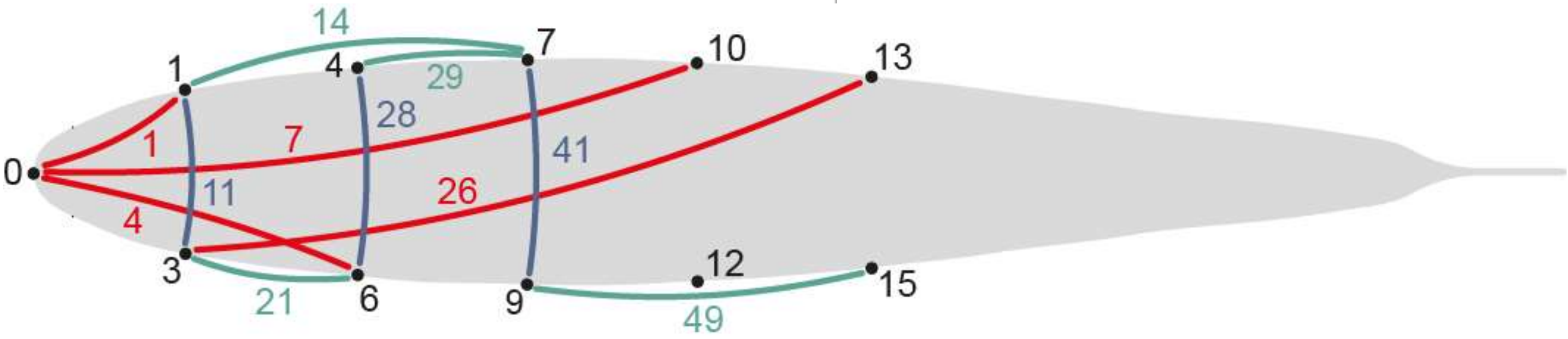


Tuhtan, J. A.; Fuentes-Pérez, J. F.; Strokina, N.; Toming, G.; Musall, M.; Noack, M.; Kämäräinen, J. K.; Kruusmaa, M. (2016). **Design and application of a fish-shaped lateral line probe for flow measurement**. *Review of Scientific Instruments*, 87 (045110), 1−8, 10.1063/1.4946765.

Sensor network outperforms Bernoulli



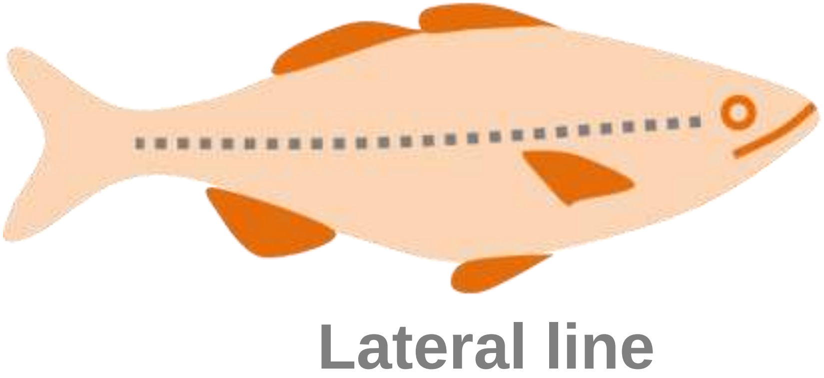


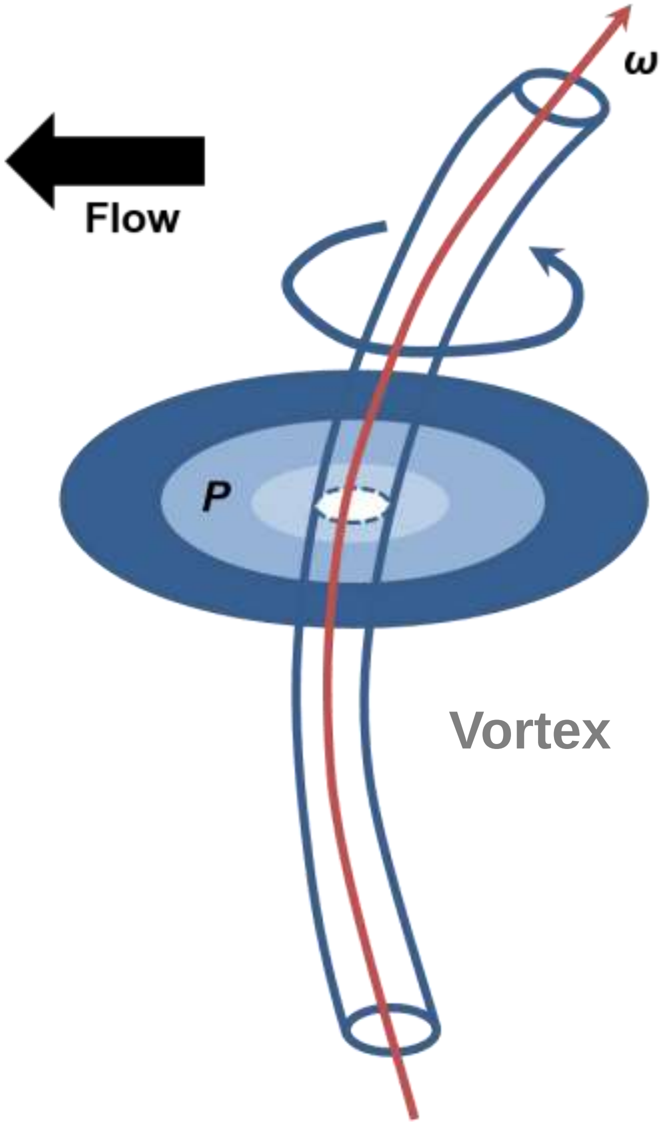


Tuhtan, J. A.; Fuentes-Perez, J. F.; Toming, G.; Kruusmaa, M. (2017). **Flow Velocity Estimation Using a Fish-Shaped Lateral Line Probe with Product-Moment Correlation Features and a Neural Network**. *Flow Measurement and Instrumentation*, 54, 1−8, 10.1016/j.flowmeasinst.2016.10.017

I got that “vortex-feeling“!

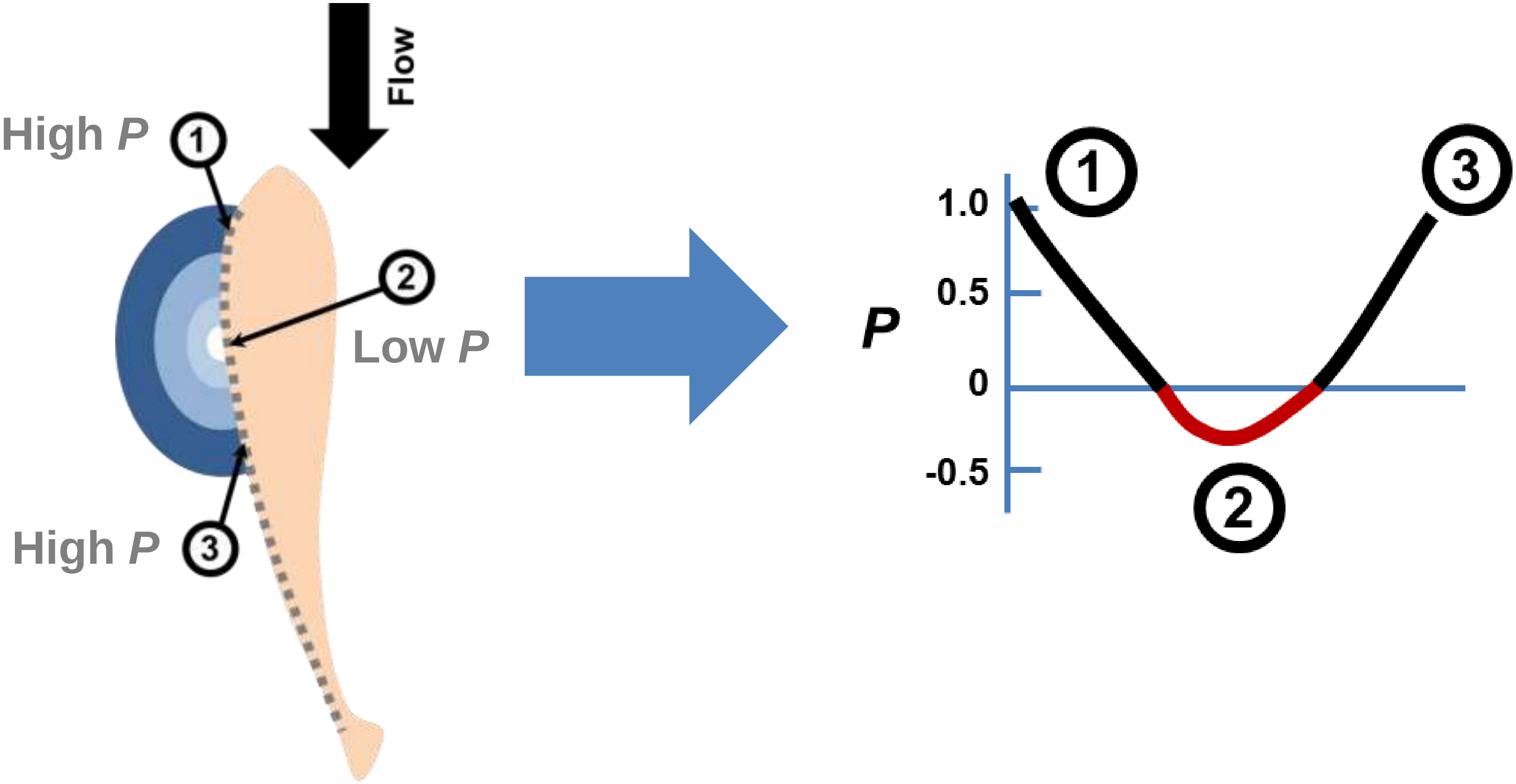
Fishes can feel vortices via a network of pressure gradients





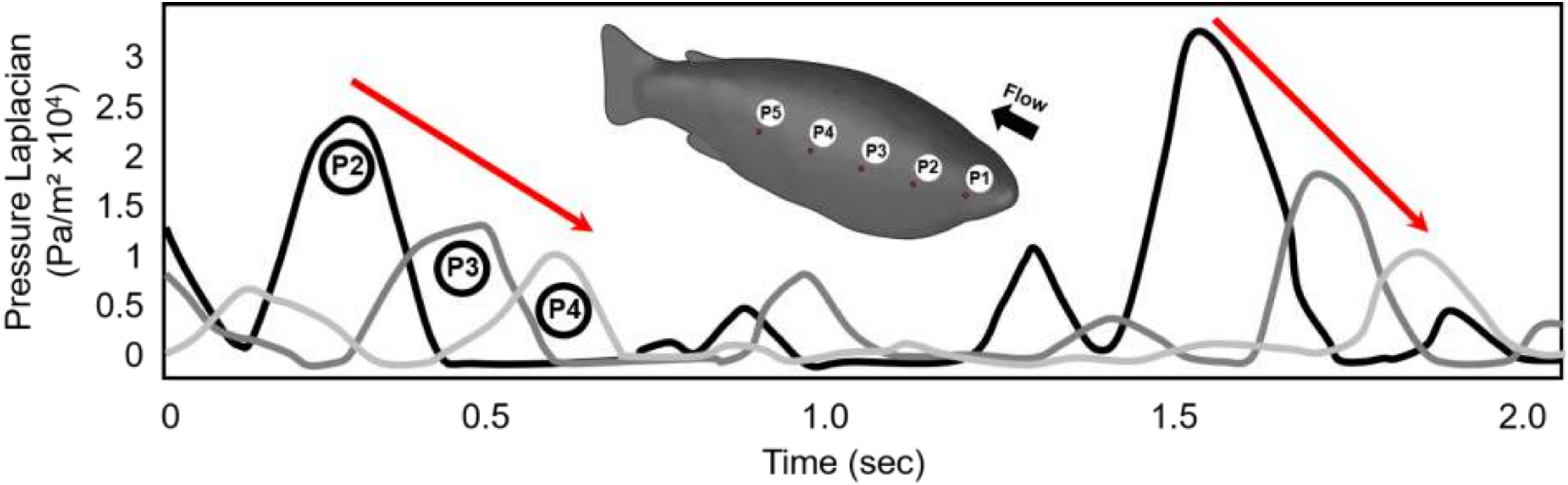
Vortex detection

Fishes feel a vortex as the pressure changes over their body



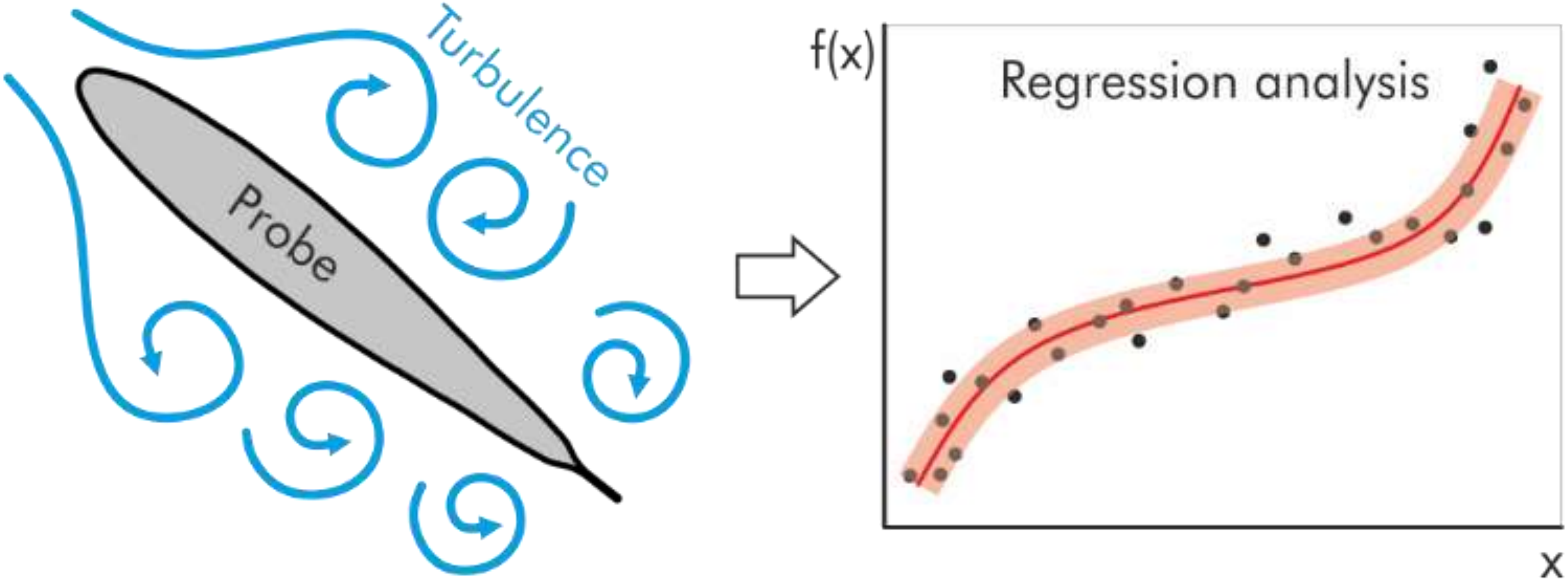
Artificial lateral line detection

A series of peaks shows that a vortex is passing over the body

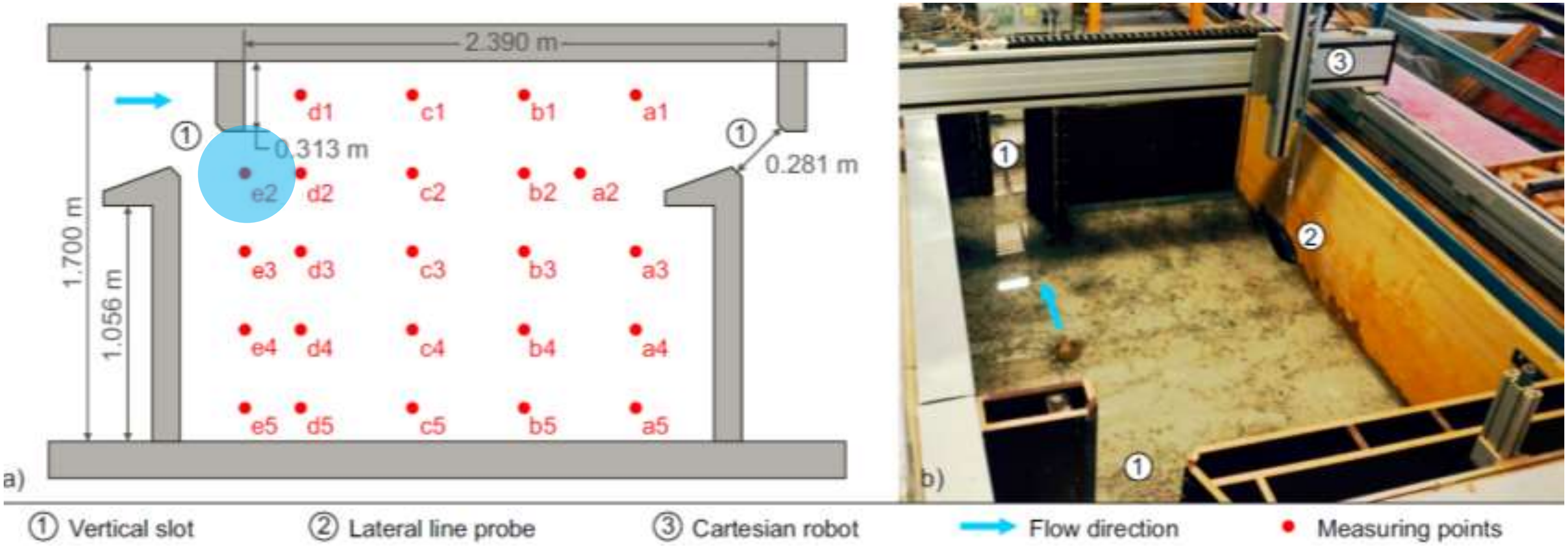


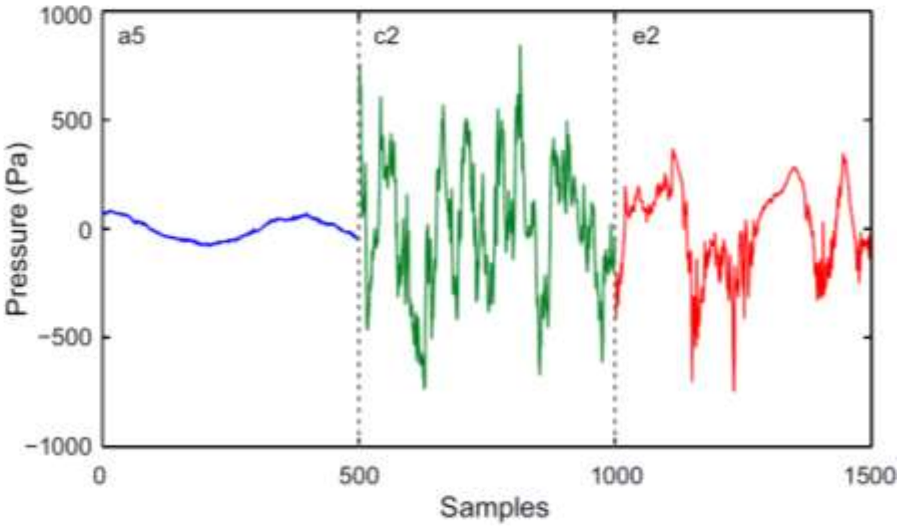
Mapping vs. measuring

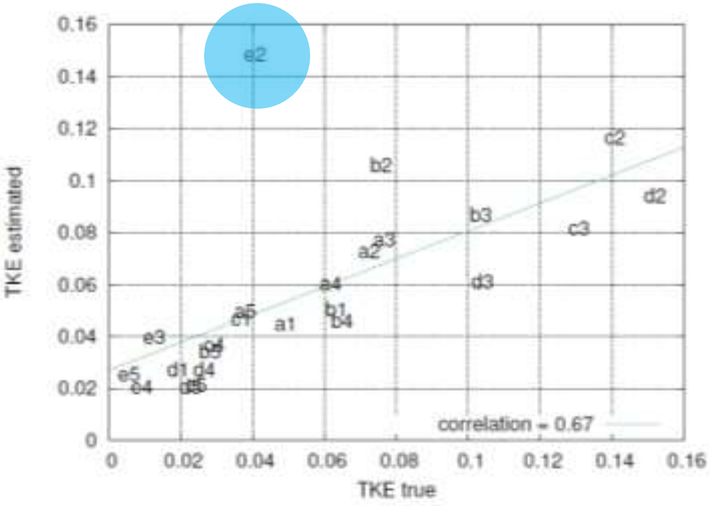
Biological sensing systems do not measure physical quantities, they **map** them via the nervous system to the brain.



Turbulence in a vertical slot fishway



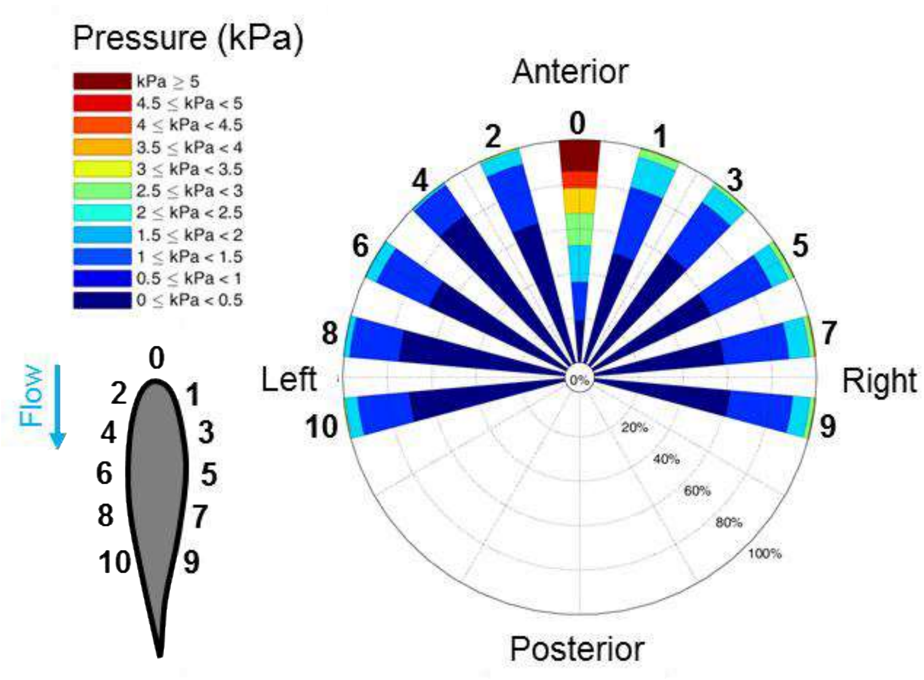


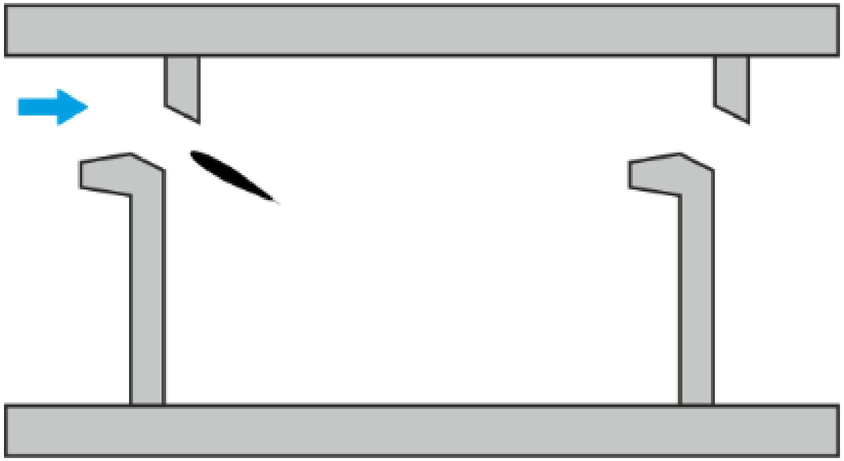


Chen, K.; Tuhtan, J. A.; Fuentes-Perez, J. F.; Toming, G.; Musall, M.; Strokina, N.; Kämäräinen, J-K.; Kruusmaa, M. (2017). **Estimation of Flow Turbulence Metrics With a Lateral Line Probe and Regression**. *IEEE Transactions on Instrumentation and Measurement* (in press)

Classification using space

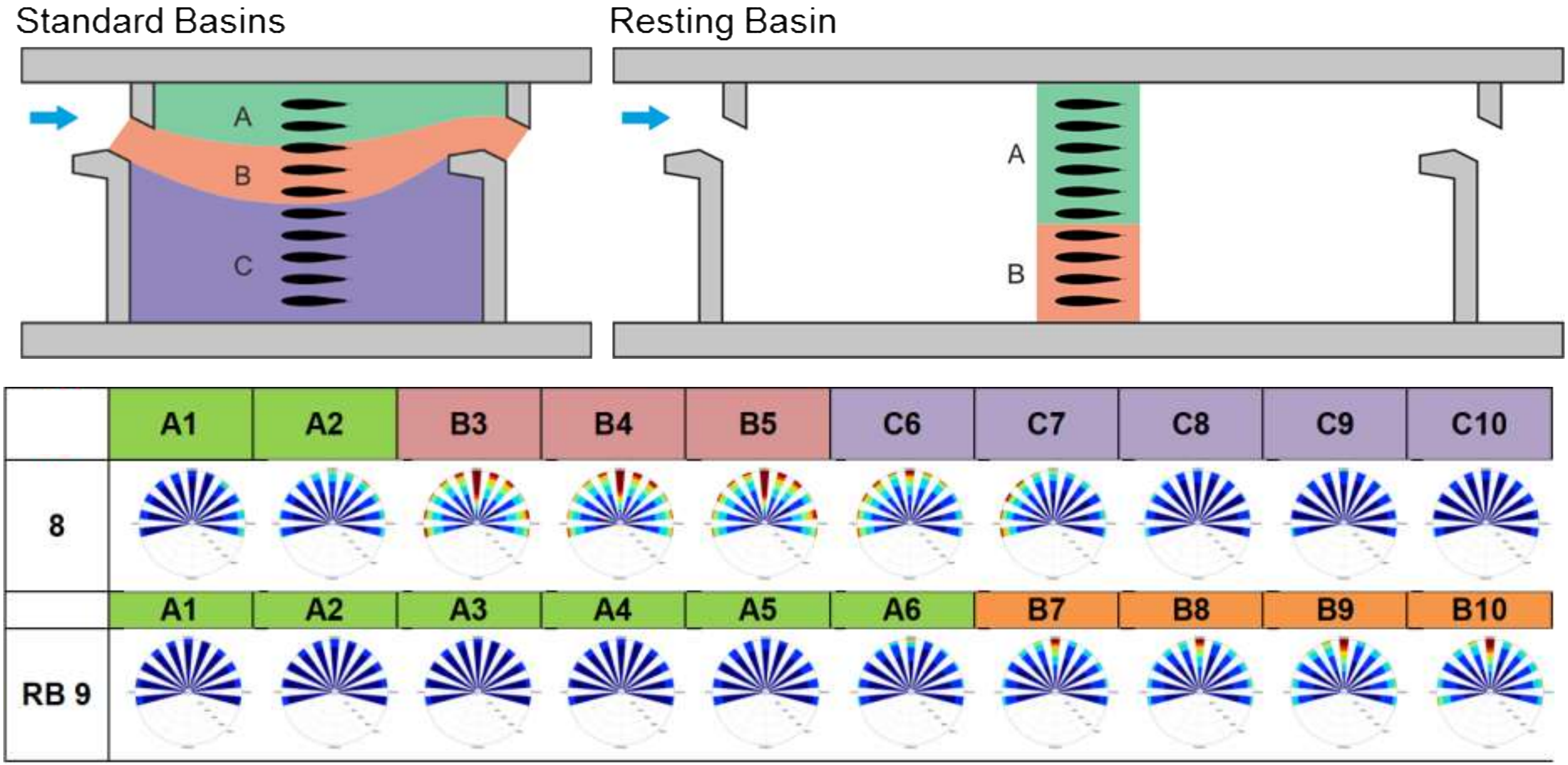
The flow around the body leaves a **hydrodynamic signature**.





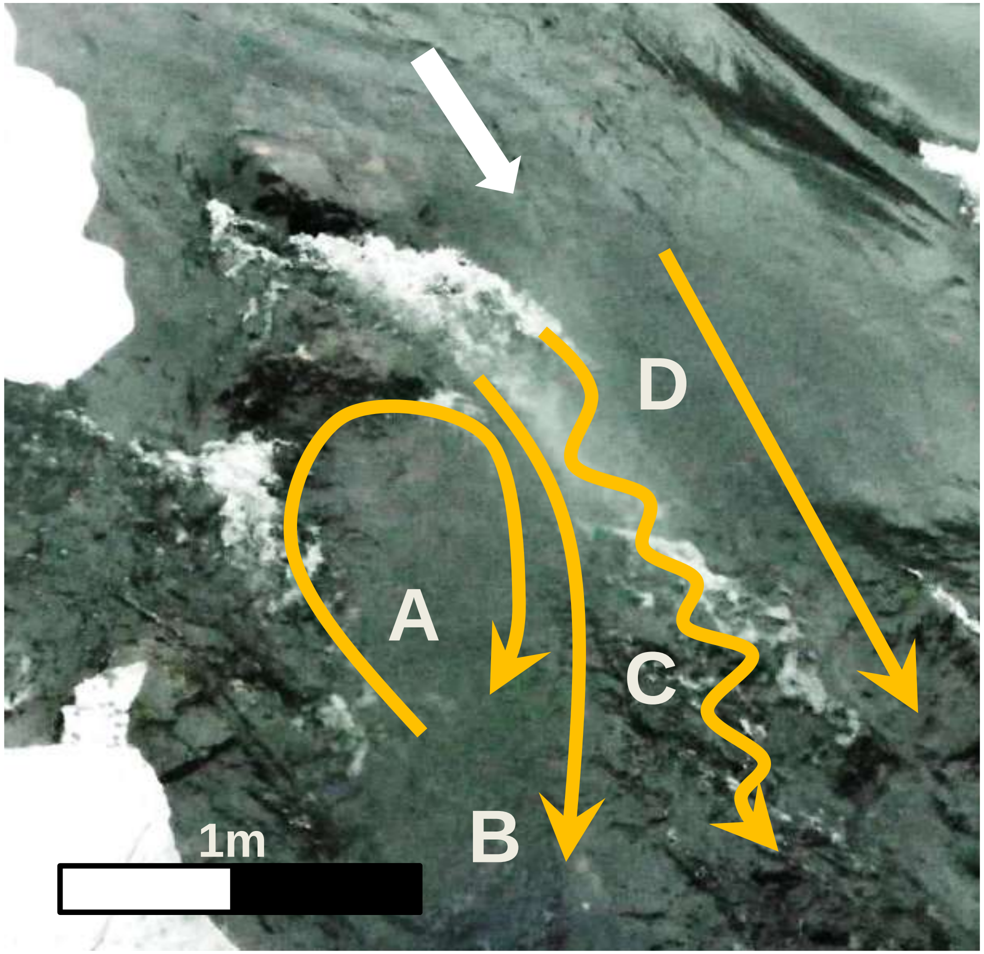
Classification using signatures

The signatures can help to identify **similar regions** in a fishway.



Classification using time

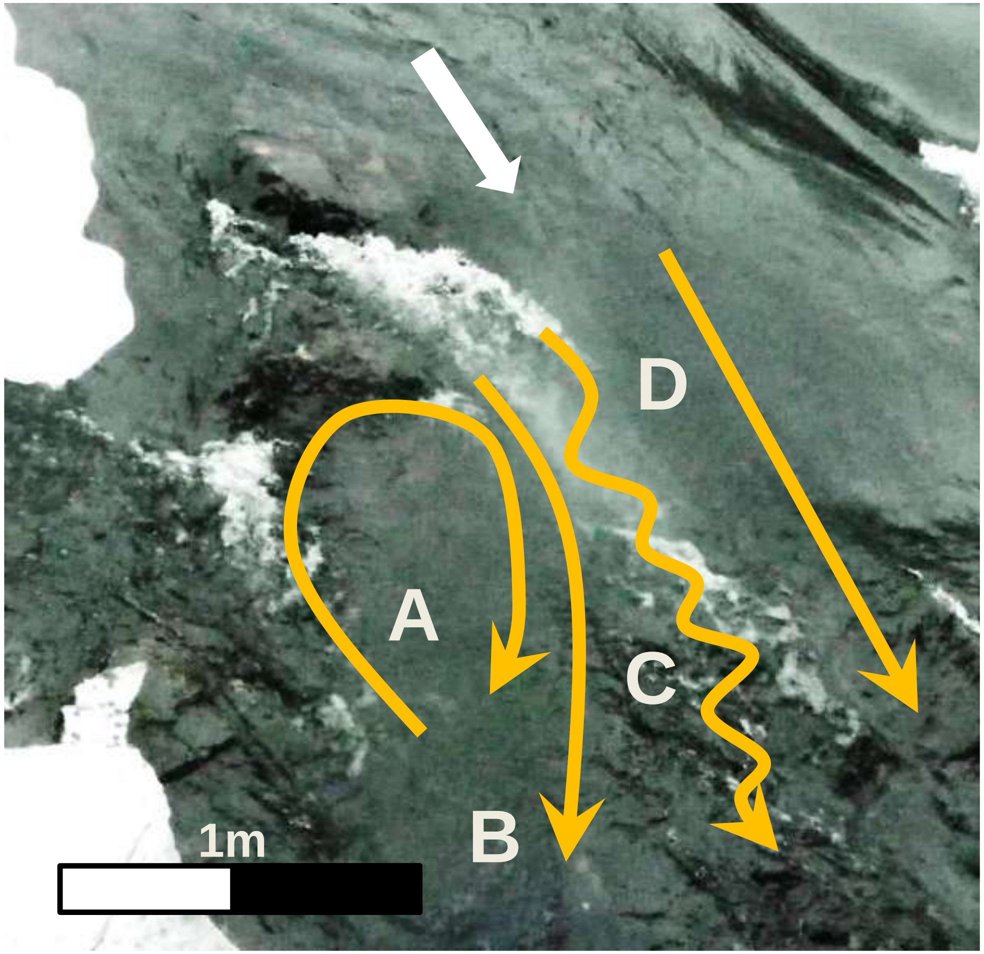
Natural flows require mapping at **multiple scales**.



A = recirculation zone
B = shear zone
C = turbulent wake
D = critical flow zone

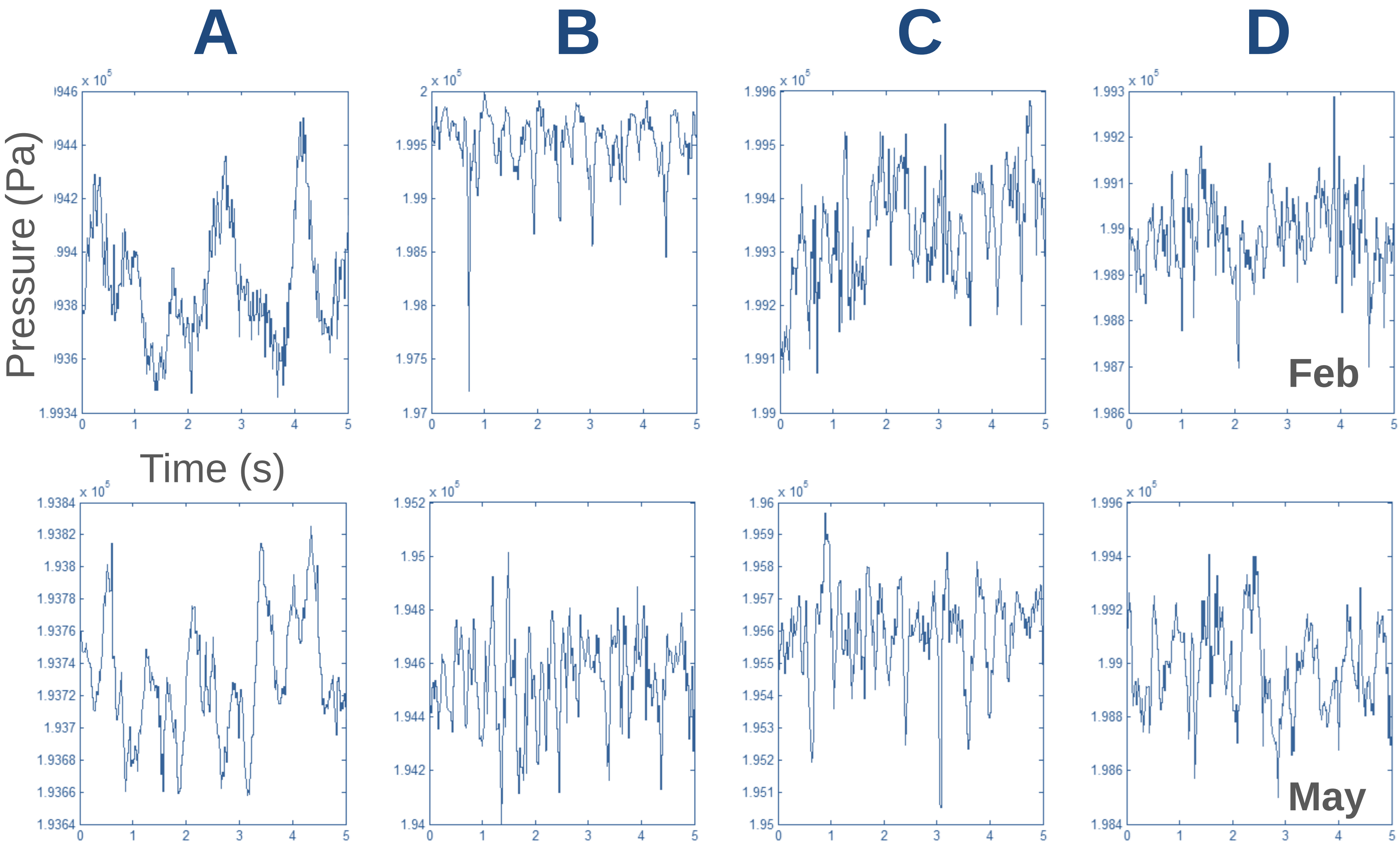
Classification using time

Natural flows require mapping at **multiple scales**.

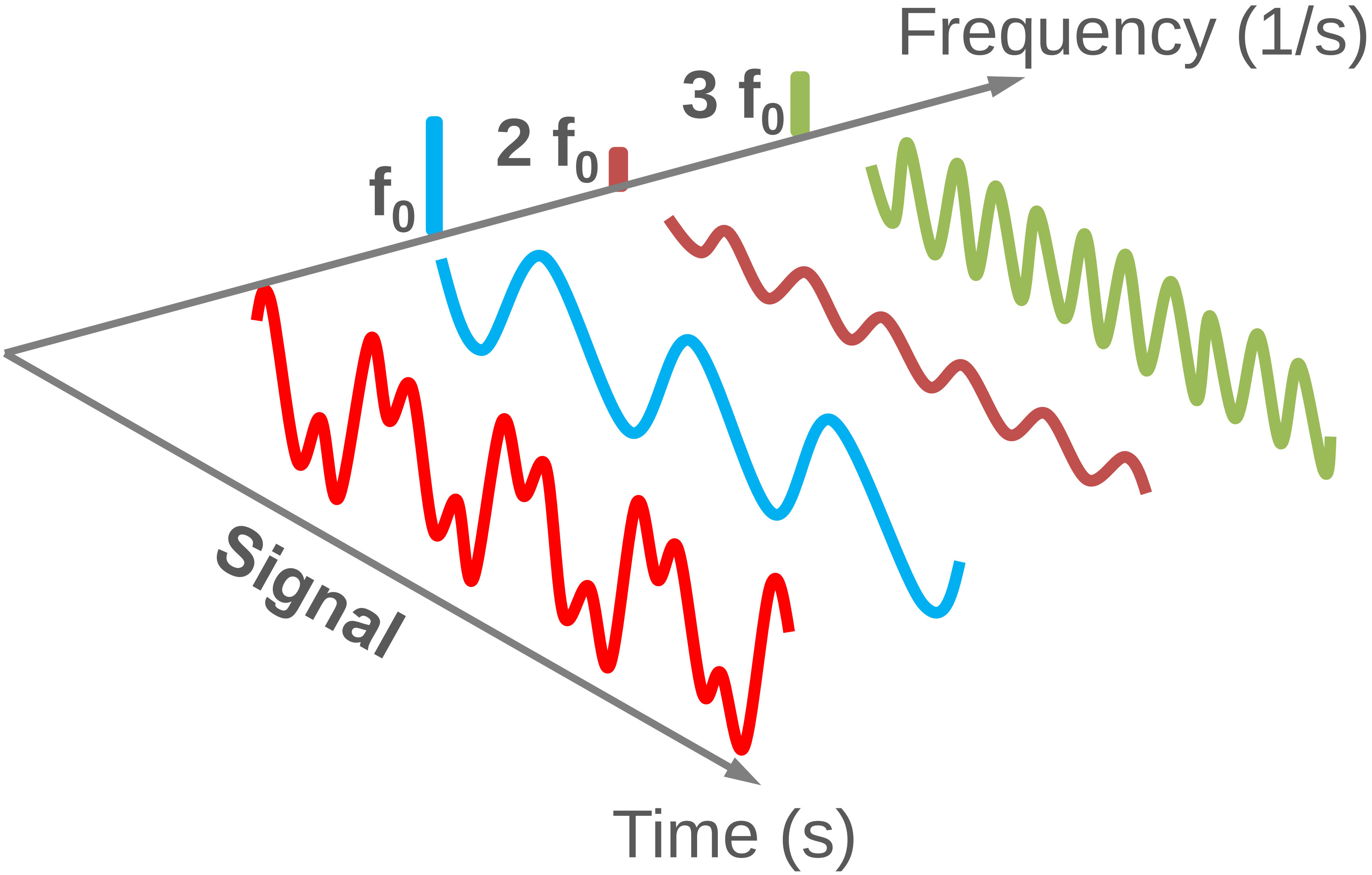


A = recirculation zone
B = shear zone
C = turbulent wake
D = critical flow zone

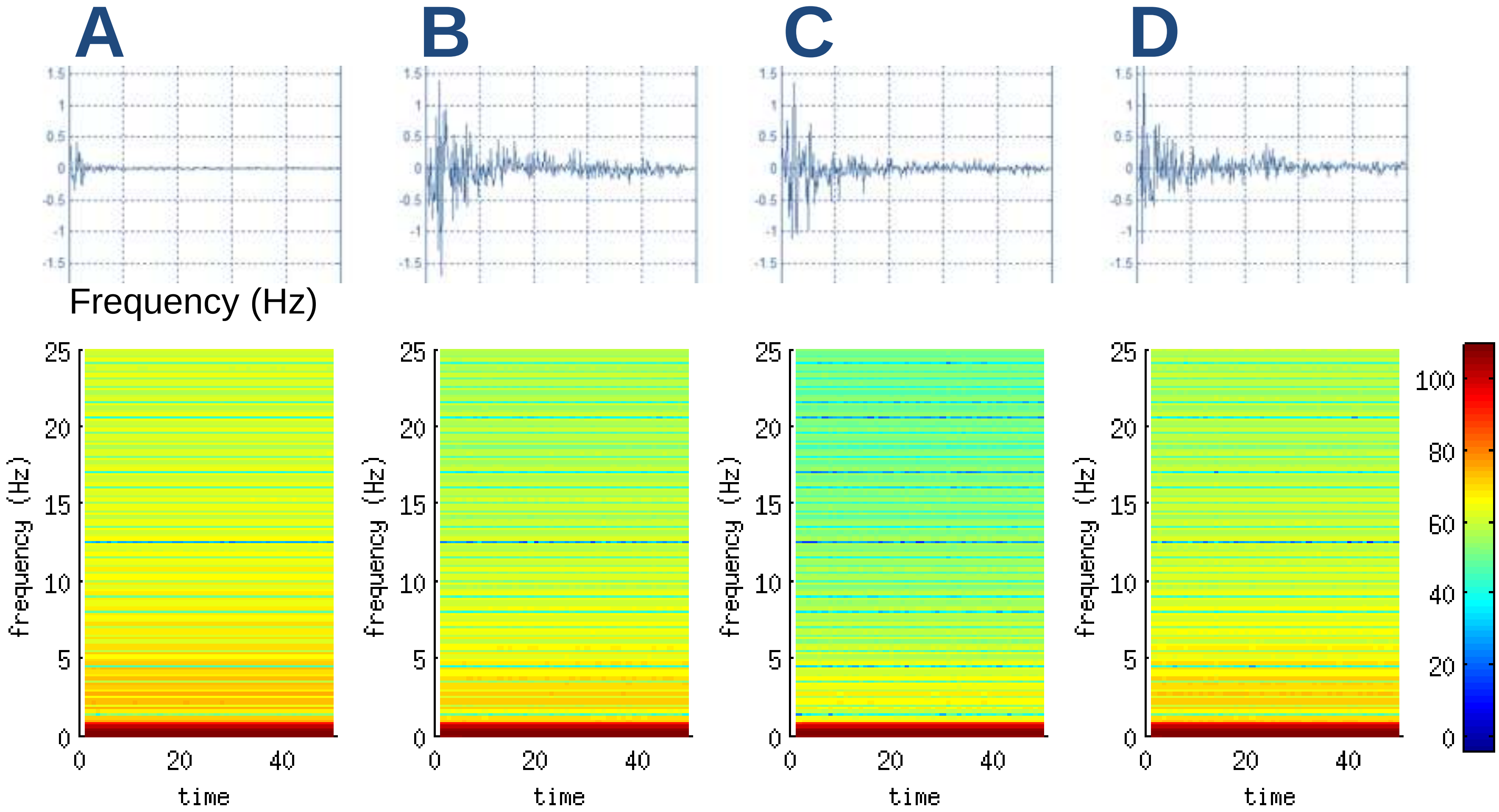
Flow Signatures – Time Domain



Time to frequency domain



Spectrogram features



86% correct classification at 2 Hz

Performed with a **Gaussian Mixture Model**

Tuhtan, J. A.; Strokina, N.; Toming, G.; Muhammad, N.; Kruusmaa, M.; Kämäräinen, J.-K. (2015). **Hydrodynamic Classification of Natural Flows using an Artificial Lateral Line and Frequency Domain Features**. 36th IAHR World Congress 2015, 28 June - 3 July, The Hague, Netherlands

Wrap-Up

1. A **fish is not a point**, in space or in time.

2. Fish use their **lateral line system** to feel the flow and retrieve flow information using spatial gradients.

3. We can use **artificial lateral lines** to sense and classify complex flows in space & time.

Thank You!

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