Electronic Visual Monitoring of Fisheries for Smart Ocean

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EDF AI-Workshop for Fishers, Japan, September 2021

UW & NOAA Electronic Monitoring Innovation Project

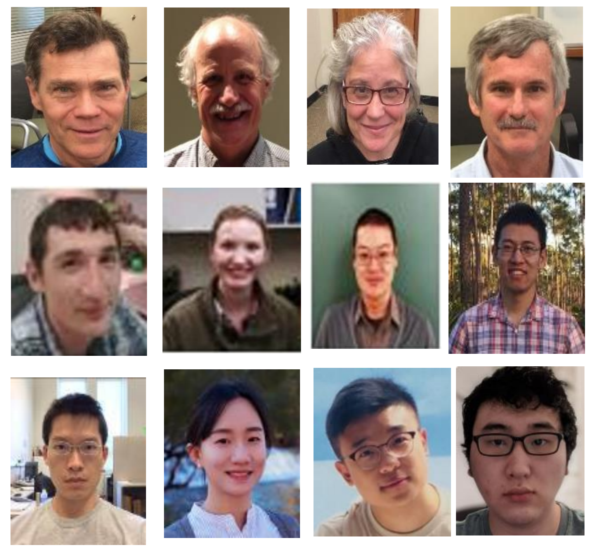
2011-2026

ALASKA FISHERIES SCIENCE CENTER

NOAA

W ELECTRICAL & COMPUTER ENGINEERING

Northwest Fisheries Science Center



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Collaborations

NORTH PACIFIC Fishery Management Council

Galveston Laboratory
A laboratory of the Southeast Fisheries Science Center.

PACIFIC STATES MARINE FISHERIES COMMISSION

IPHC

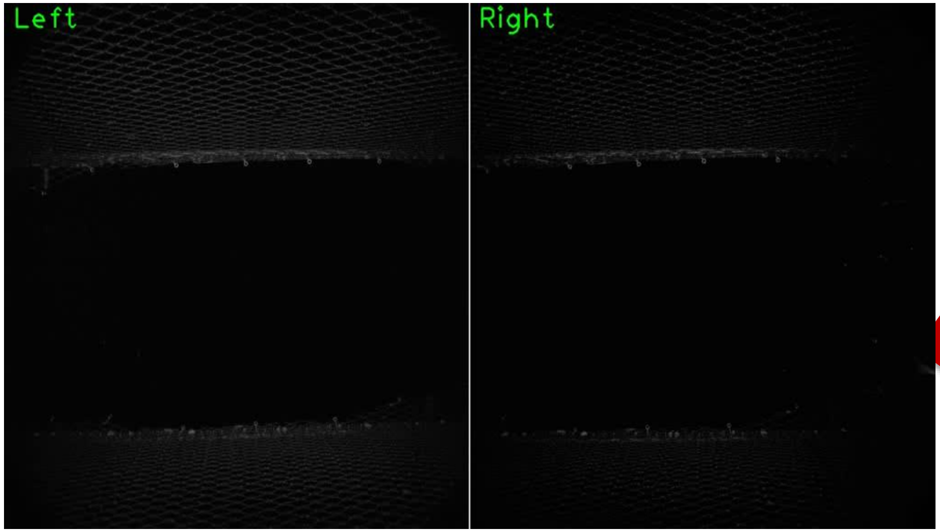
ALASKA DEPARTMENT OF FISH AND GAME

Motivation

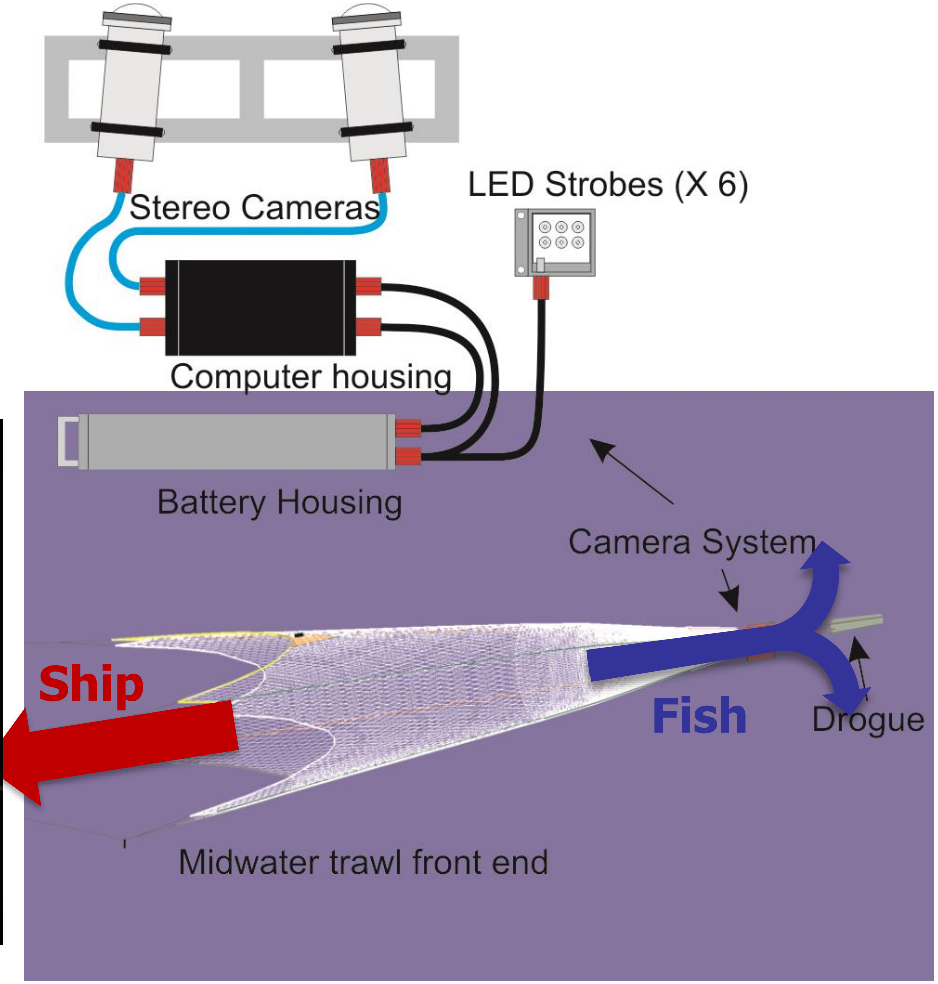
- Fisheries are a multi-billion dollar global industry that requires management tactics for long-term sustainability.
- Camera systems for monitoring fish abundances become a common practice in conservation ecology and stock assessment.

NOAA Alaska Fishery Science Center (AFSC) Cam-Trawl

- Combination of trawl and a stereo camera system
- Allowing fish to pass unharmed after sampling

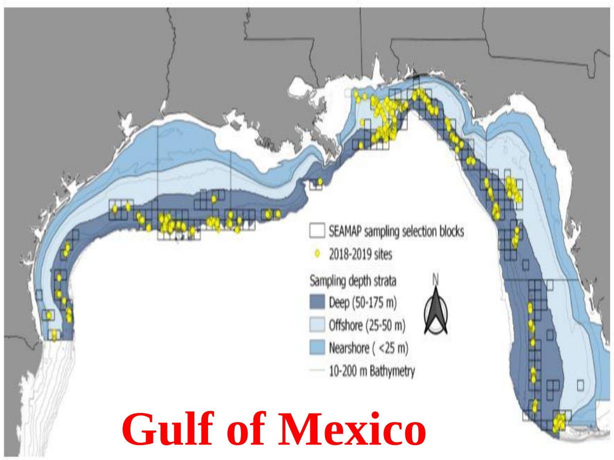


[K. Williams, et al, 2010]



NOAA Southeast Area Monitoring & Assessment Program (SEAMAP)

- Since 1992, 45+ million files, 167+ TB of data, with an annual increaseof~13TB



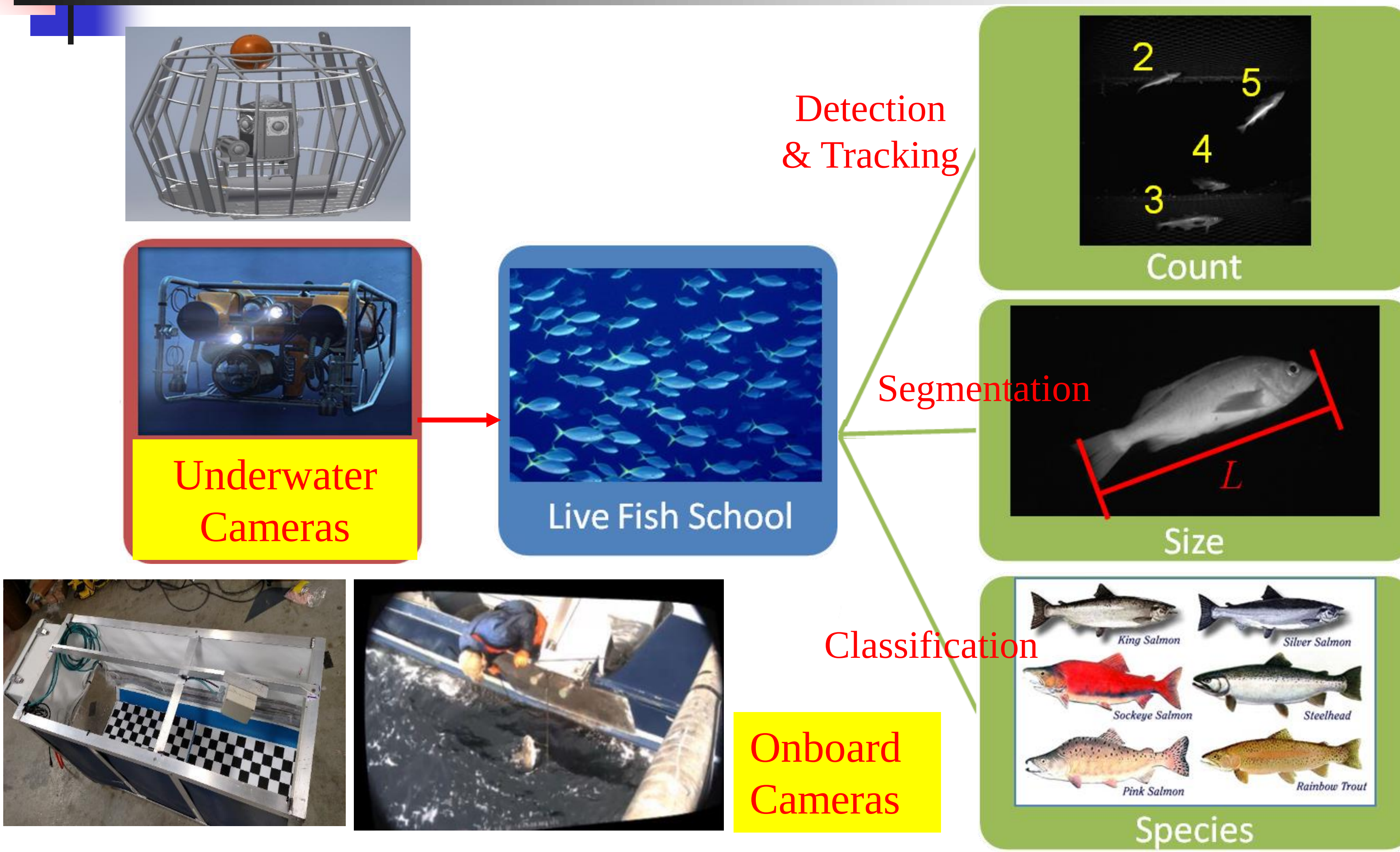
Electronic Monitoring of Fishing Activities

- Electronic monitoring (EM) system on federal fisheries
  - Monitor the fish species and size
  - Near real-time reporting (via satellite), regulation compliance

Chute-based On-Board Monitoring

Longline Rail-Catch Monitoring

Big Fisheries Data for Smart Ocean

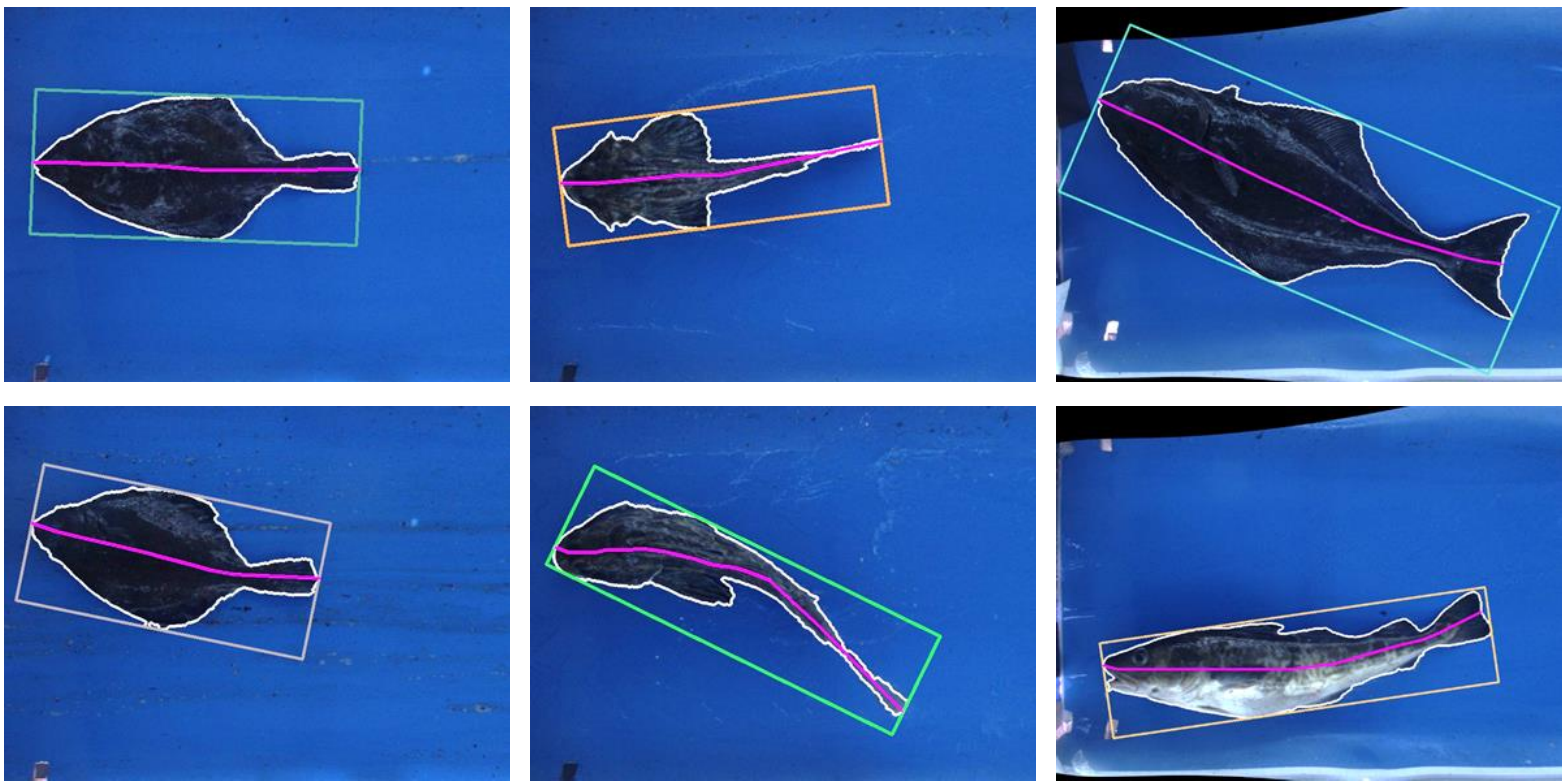


Outline

- Electronic Visual Monitoring of Fishery
- **Chute based Electronic Monitoring**
- Longline Rail-Catch Electronic Monitoring
- Conclusion

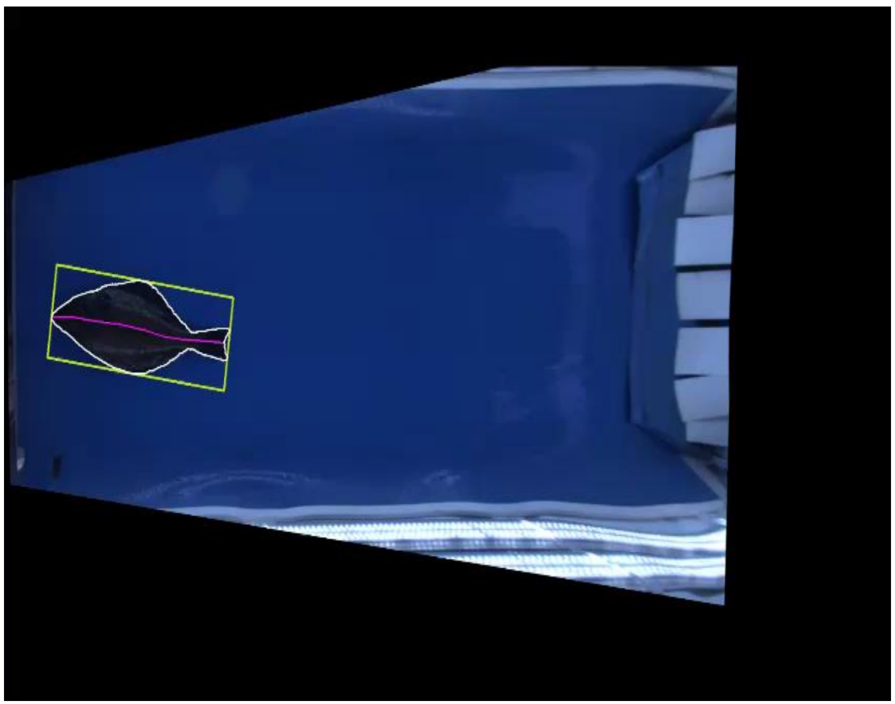
Fish Length Measurement

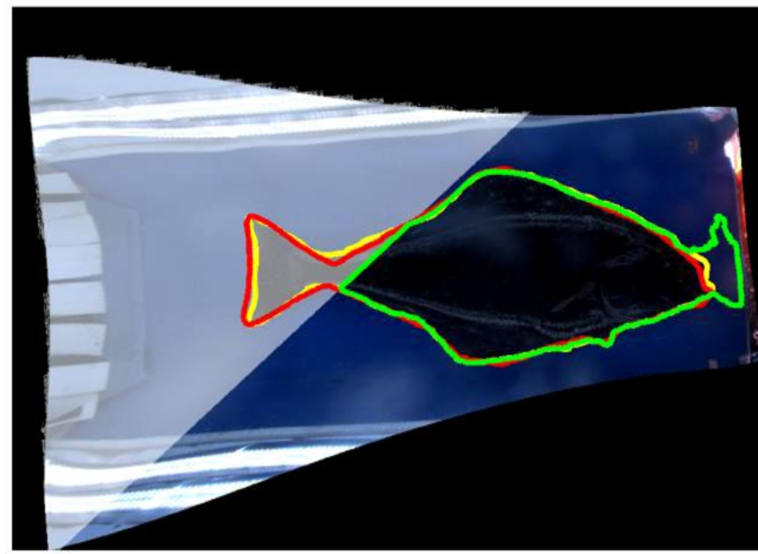
- Many variations of deformations → morphological midline



Different orientation **Curved** **Forked tail**

Length Measurement Examples





Mean of Absolute Error of 11 Species of Fishes (3571 samples) – 1.49%

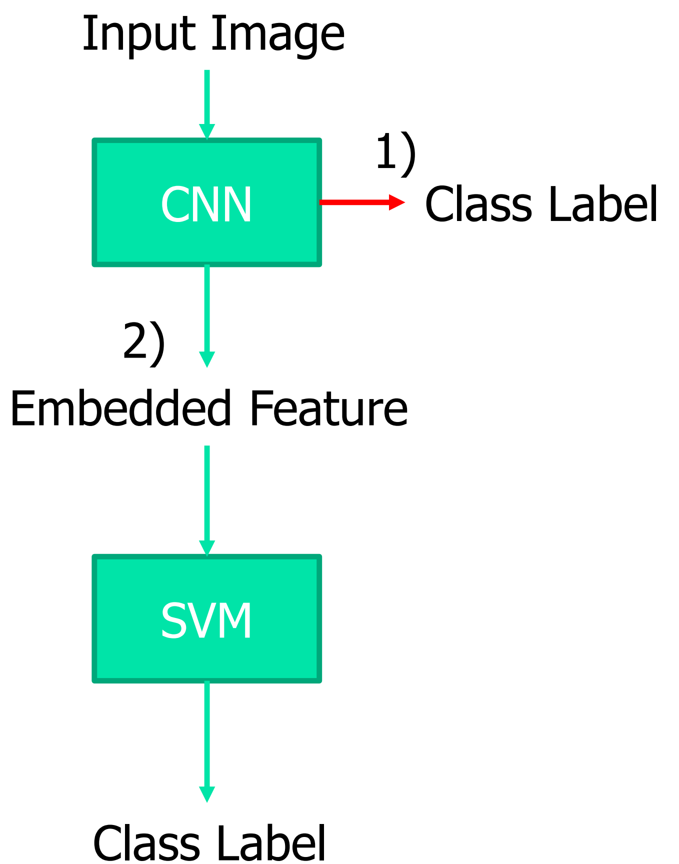
Tsung-Wei Huang, et al, IEEE ICASSP 2016

Fish Counting & Length Estimation in Slummy Conditions

Deep Learning based Fish Species Identification

- Training Data (201 classes, 2015+2016+2019)
  - 11557 (x150 augmentation)
- Testing Data
  - 1412

Method	Accuracy (201 classes)
BoF (7168-dim) + SVM	89.1%
CNN (Inception ResNet v2)	91.7%
CNN (1536-dim) + SVM	92.9%



Re-Visit Fish ID Tasks

- Datasets
  - 2015 chute data (8835 images with 27 classes)
  - 2016 chute data (5032 images with 27 classes)
- Same dataset split into training and testing

Training Data	Testing Data	Cross Validation	Accuracy (%)
2015	2015	10-fold	96.1
2016	2016	10-fold	98.5
2015+2016	2015+2016	10-fold	96.9

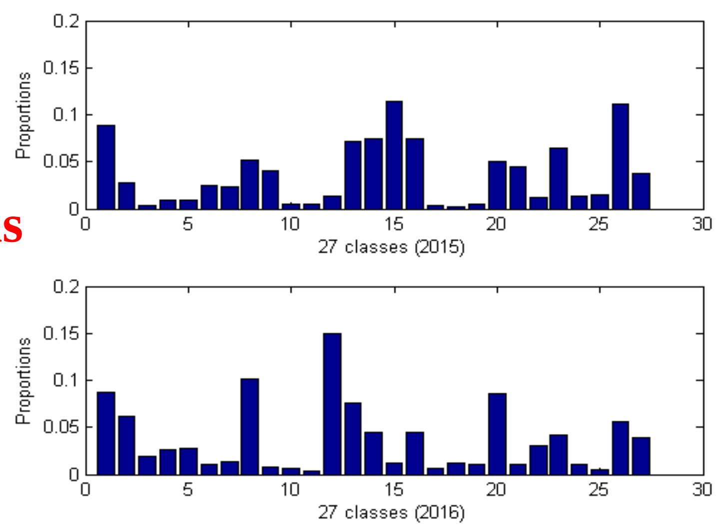
Training Data	Testing Data	Acc (%)
2015 dataset (5%)	2015 dataset (95%)	83.9
2016 dataset (5%)	2016 dataset (95%)	86.6
2015 dataset (100%)	2016 dataset (100%)	69.5
2015 dataset+2016 dataset (5%)	2016 dataset (95%)	88.1

Some Problems of Supervised Learning

- If large (domain or label shifts) difference between training and testing datasets
  - Slight species variations
  - Different camera color responses
  - Different distributions of species

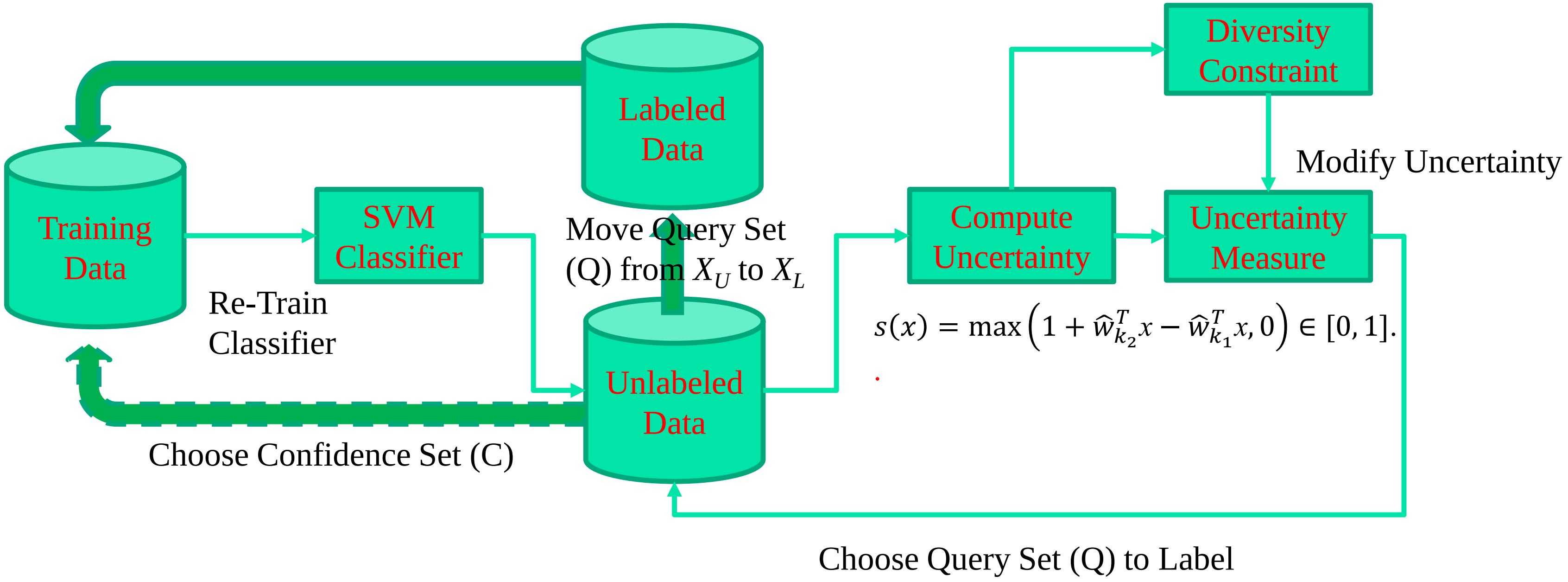
Fish ID	Fish Name
1	Arrowtooth Flounder
2	Atka Mackeral
3	Bathymaster Signatus
4	Berryteuthis Magister
5	Blackspotted Rockfish
6	Dover Sole
7	Dusky Rockfish
8	Flathead Sole
9	Giant Grenadier
10	Gorgonocephalus Eucnemis
11	Harlequin Rockfish
12	Northern Rock Sole
13	Northern Rockfish
14	Pacific Cod
15	Pacific Halibut
16	Pacific Ocean Perch
17	Pacific Octopus
18	Paragorgia Arborea
19	Prowfish
20	Rex Sole
21	Sablefish
22	Shortraker Rockfish
23	Shortspine Thornyhead
24	Strongylocentrotus sp
25	Sturgeon Poacher
26	Walleye Pollock
27	Yellow Irish Lord

Species Distributions



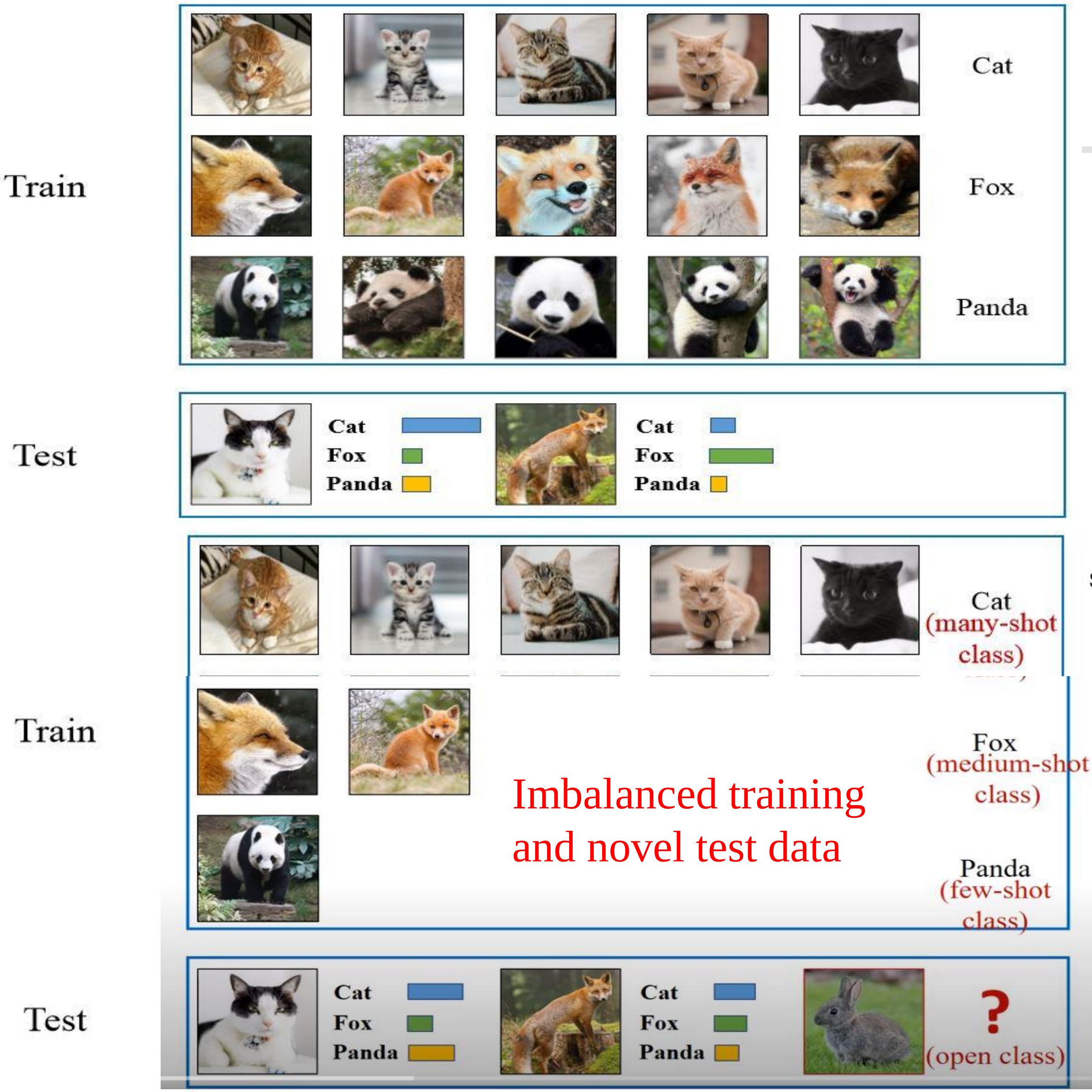
Active (Query) Learning for Domain Adaptation

- Goal: iteratively select informative samples for human labeling to improve the classifier performance



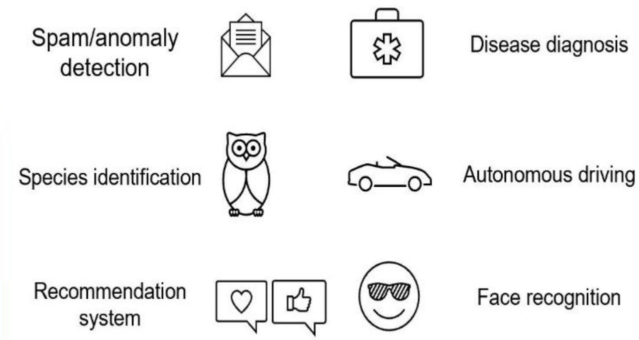
- 2015 dataset+2016 dataset (5%): 88.1% → 96.8%

Real World Object Recognition

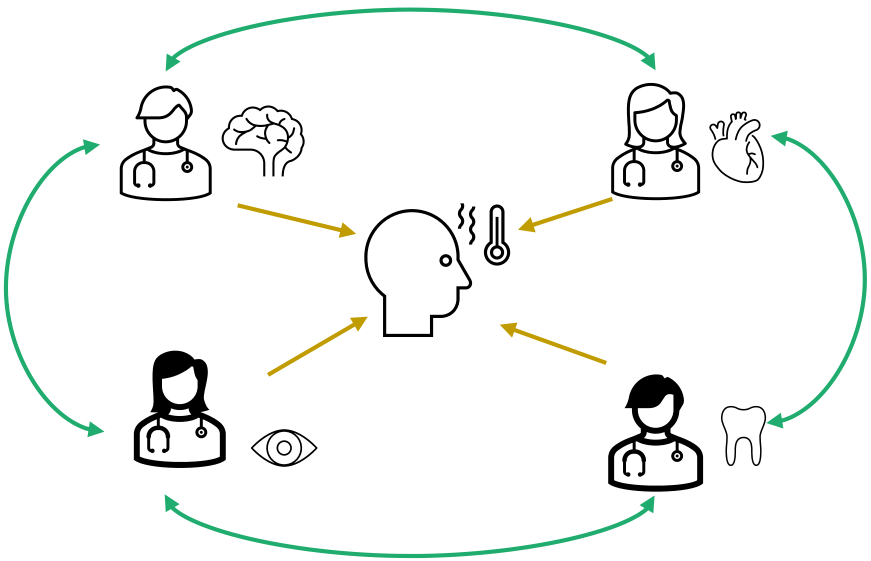


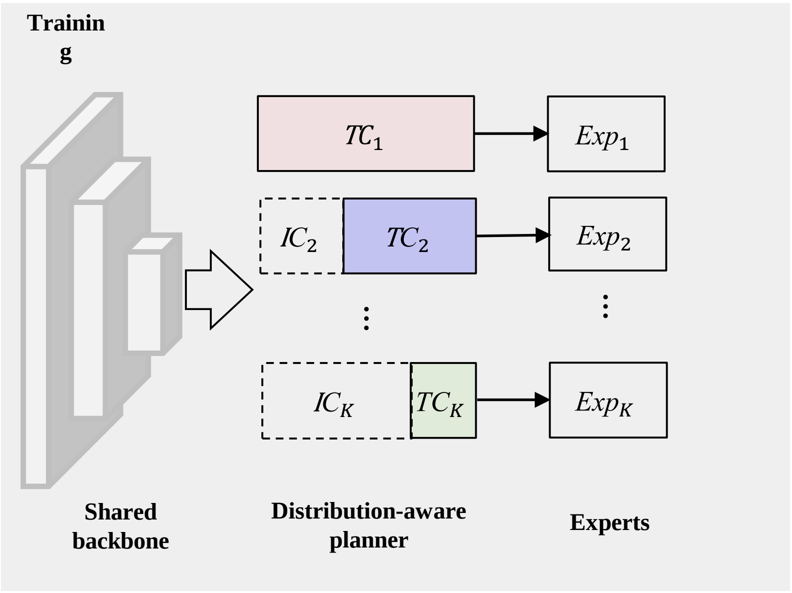
Long-Tailed Recognition (LTR)

Open-Set Recognition (OSR)



ACE: Ally Complementary Experts for LTR





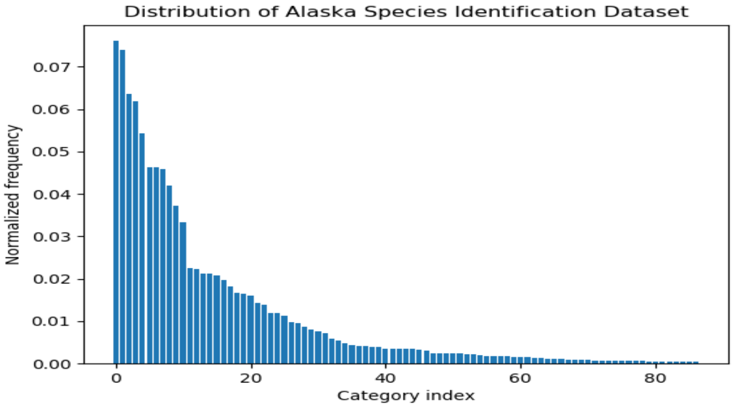
TC: Target categories **IC:** Interfering categories

- Involve multiple specialists' insights
- Panel discussion to exclude interfering potentials

Jiarui Cai, et al., "ACE: Ally Complementary Experts for Solving Long-Tailed Recognition in One-Shot," ICCV 2021

Alaska Chute Fish Dataset

- Alaska species ID dataset: 26.4k images for 87 classes
- Many-shot (>100 samples): 38 classes
- Medium-shot (>20 and <=100 samples): 33 classes
- Few-shot (<= 20 samples): 16 classes



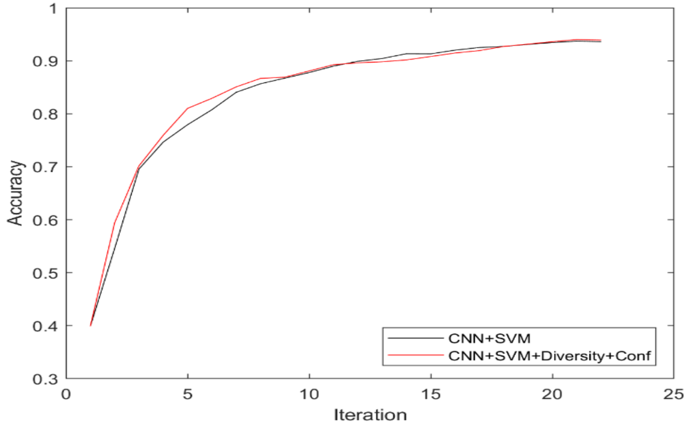
- Imbalance factor = N_{max}/N_{min}= 193.5

	Top1 acc	Top 2 acc	Top 3 acc	Many	Medium	Few
ACE	94.48%	97.70%	98.39%	98.42%	96.97%	80.00%

Active Learning for New Classes Discovery

- Non-Query Learning
- 43-class (42+1 others)
  - Training, 6042 images
  - Testing, 698 images
  - 90% samples used in the training.
  - Accuracy = 94.5%.

- New Class Discovery
- From 27 to 42 classes
  - 5% samples used in the training.
  - Accuracy = 93.9%.



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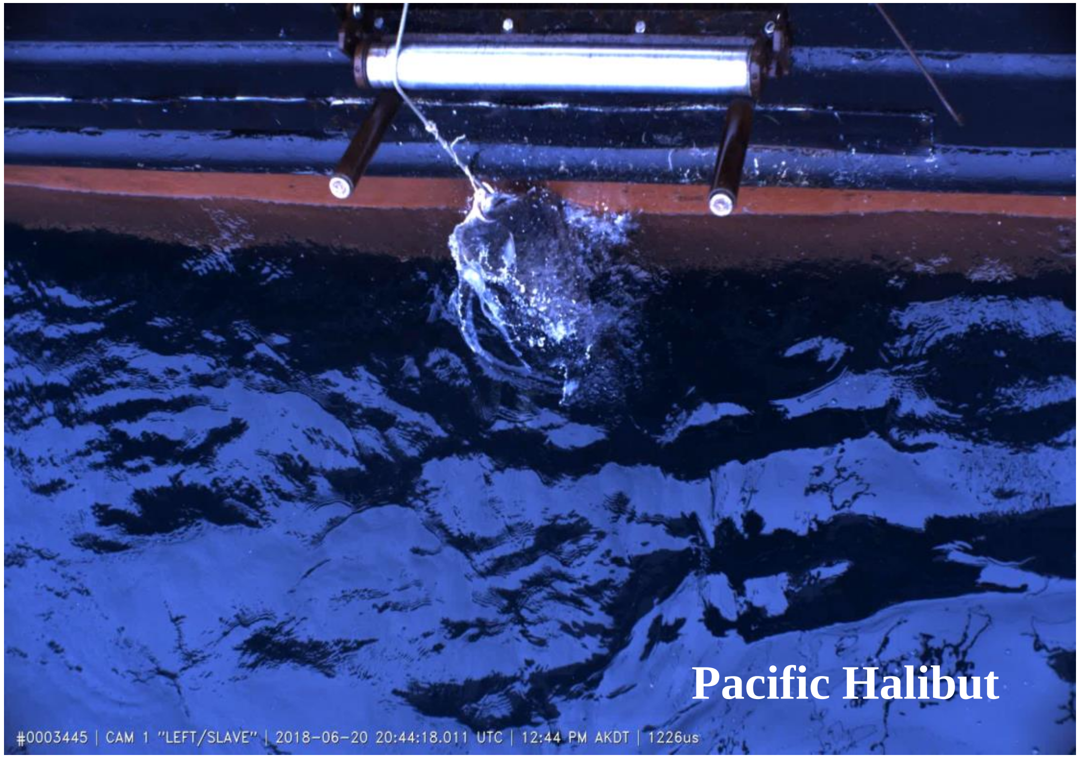
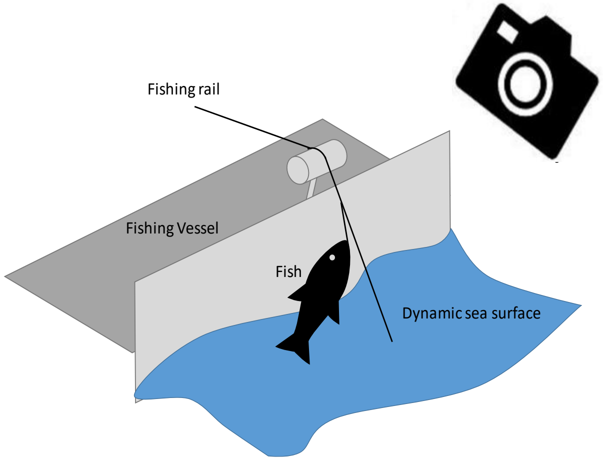
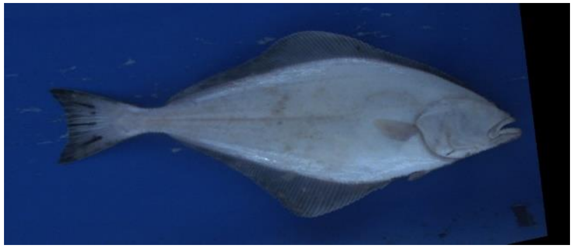
Longline Rail Fishing

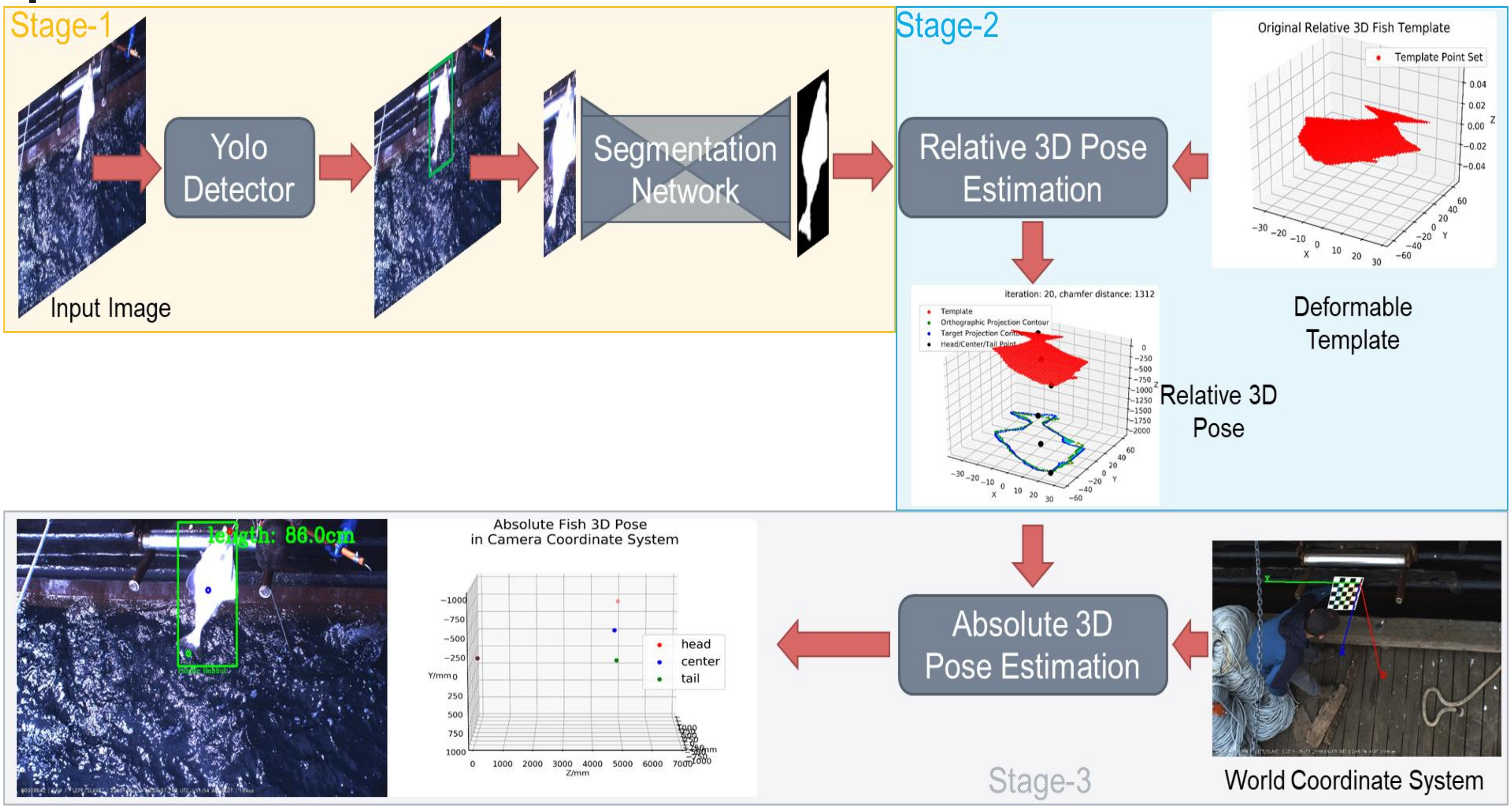






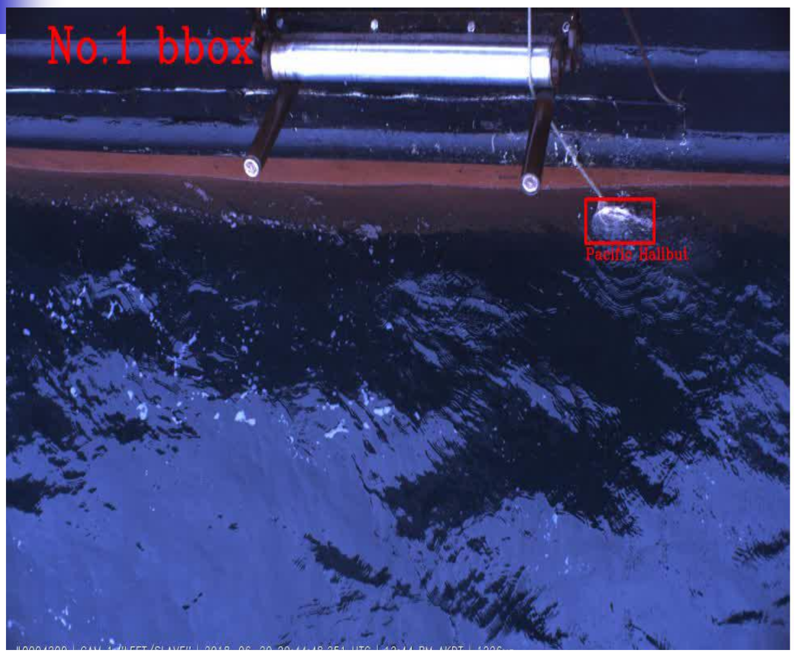
- Absolute 3D Pose Estimation and Length Measurement of Severely Deformed Fish from Monocular Videos in Rail Fishing

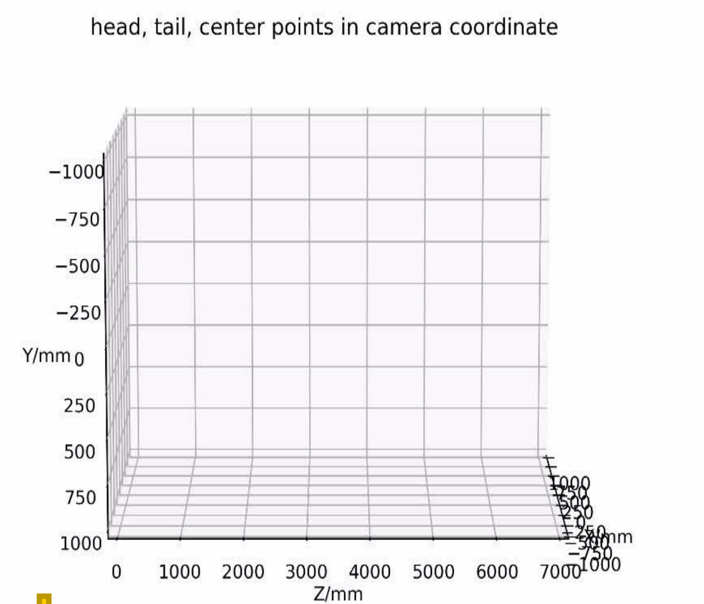
Fish Tracking (Counting) and Length Measurement



Jie Mei, et al., "Absolute 3D Pose Estimation and Length Measurement of Severely Deformed Fish from Monocular Videos in Longline Fishing," IEEE ICASSP 2021, Toronto, Ontario, Canada, June 2021

Track based Length Measurement from Absolute 3D Pose Estimation

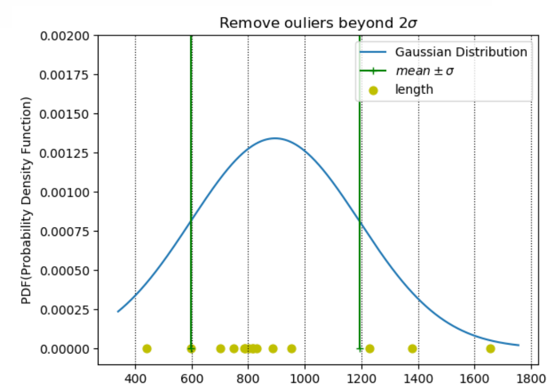




Method	Bias(mm)	EMD(mm)	RMSD	KL
Stereo	-40.5	46.0	7.9%	0.26
BFS	-10.2	24.2	5.6%	0.11
BFS w/o Bending	-55.4	60.0	7.9%	0.28
Ours w/o Bending	-95.4	99.3	10.4%	0.53
Ours	-9.3	43.1	7.3%	0.23

738 fish samples

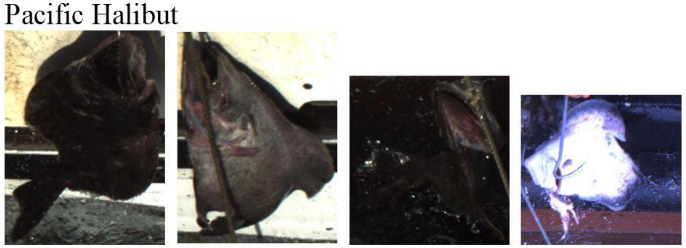
Z=0 plane is image plane



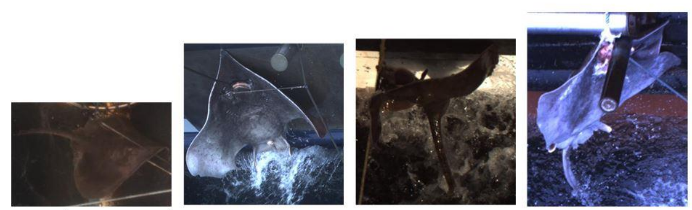
Rail Fishing Species ID

- Choice of feature
  - Discriminative features
  - Robust to deformation of fish and viewing angle
- Challenges
  - High visual similarity among fish species
  - Large within-class variation due to pose and shape changes

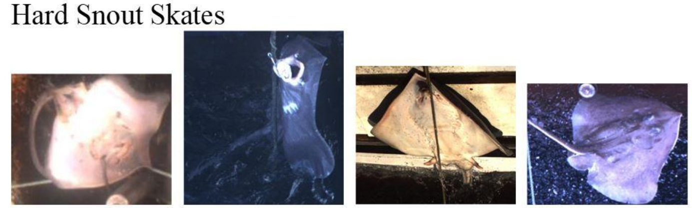
Pacific Halibut



Arrowtooth Flounder



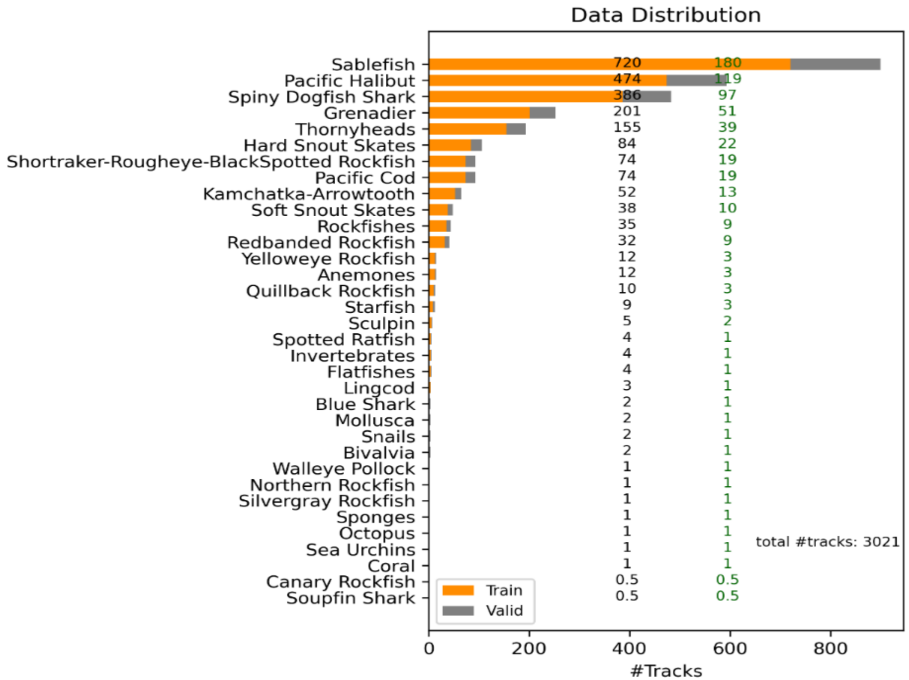
Hard Snout Skates



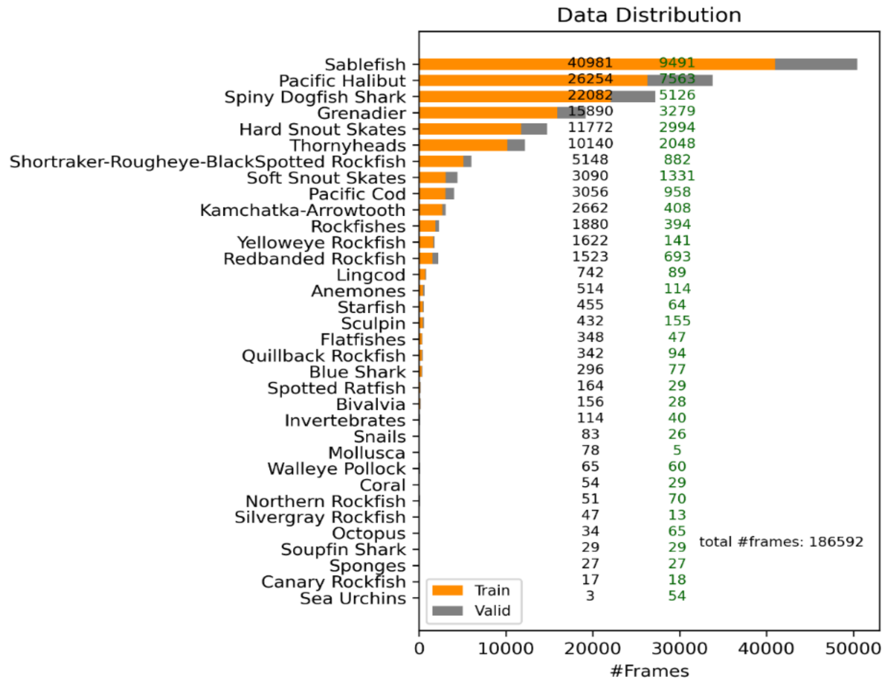
Soft Snout Skates

Track-based Species ID

- Track-based data split for train/evaluation



Track #

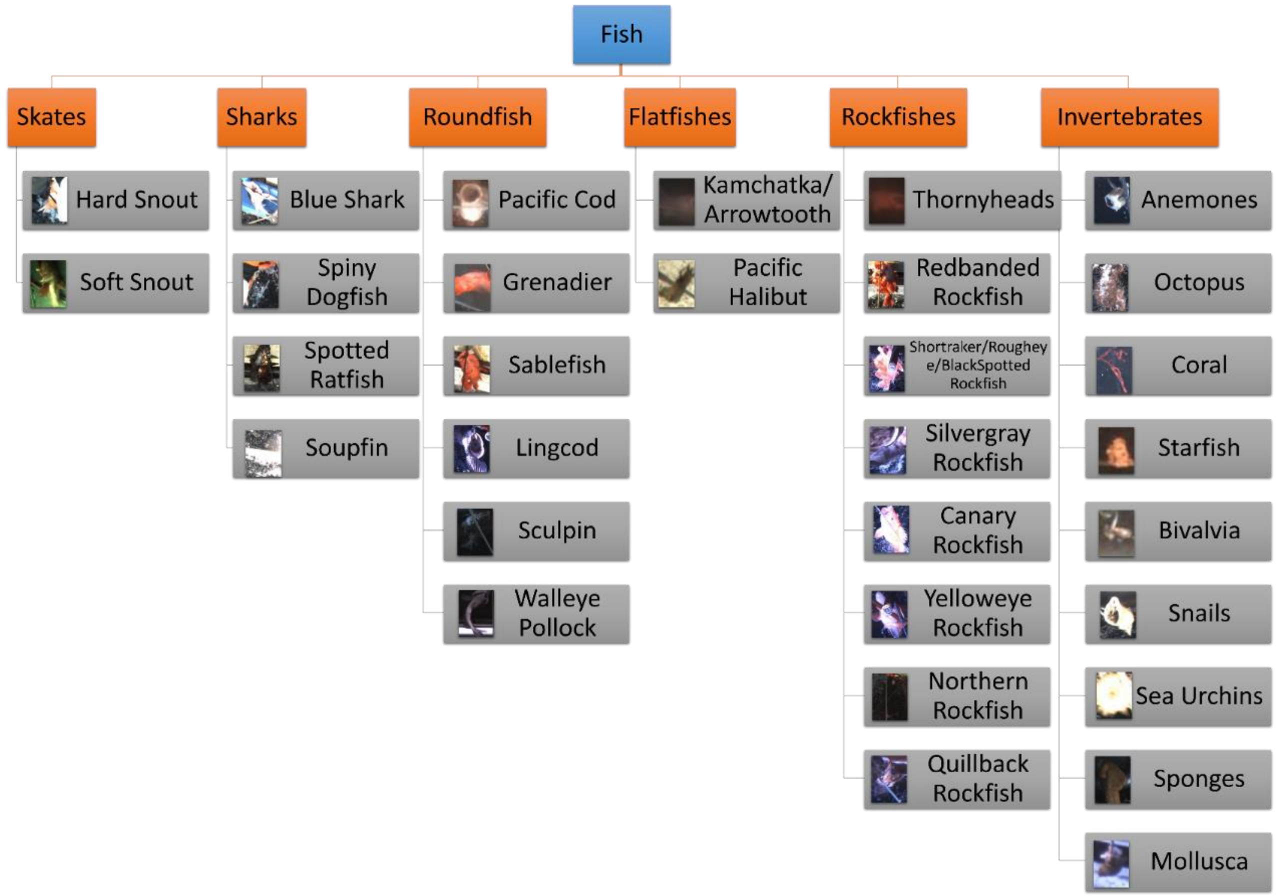


Frame #

Hierarchical Species ID

Level-1 (6 groups)

Level-2 (31 species)



Experimental Results

Ablation study

Model	Unit	Level-1	Level-2 A	Level-2 B	Level-2 C
Baseline	img	-	-	78.3	-
Scheme-1	img	86.3	77.4	77.4	82.0(8567, 27393)
	*video**	93.2	86.5	86.6	93.2(298, 319)
	video	93.4	86.5	86.8	93.4(293, 324)
Scheme-2	img	88.4	79.9	80.0	84.6(8660, 27300)
	*video**	94.3	88.6	88.9	94.3(329, 288)
	video	94.9	88.9	88.8	94.9(328, 289)
Scheme-3	img	91.0	82.3	82.3	86.3(5830, 30130)
	*video**	96.3	90.6	90.3	96.3(286, 331)
	video	**96.4**	**90.9**	**90.9**	**96.4**(293, 324)

Scheme-1: 7 head, w/o multiplication, Loss1
Scheme-2: 7 head, w/ multiplication, Loss1
Scheme-3: 7 head, w/ multiplication, Loss2

'video' : Average confidence score among 31 species to pick one predicted species for each track.
'video∗ ': Majority vote to pick one predicted species for each track

A: max score from level-1, then max score from level-2
B: max score out of 31
C: max score out of 31, but can stop at level-1(threshold 0.91)

Conclusion

- Real-time sensing, communication, computing and control is being realized everywhere -- smart city, smart car, intelligent house, smart manufacturing, etc
- Big data allow machine learning and AI to be effective and possibly real-time response, thanks to powerful communication and computing
- Every fishing boat or underwater camera on the ocean is an IoT sensor for exploration – big fishery data
- From analyzing these big fishery visual data -- a step toward Smart Fishery and Smart Ocean