BugID: Rapid-Throughput Insect Population Counting Using Computer Vision

Students: N. Larios, H. Deng, W. Zhang, M. Sarpola, J. Yuen, S. Ruiz Correa

Faculty: R. Paasch, A. Moldenke, D. A. Lytle, E. Mortensen, L. G. Shapiro, T. G. Dietterich

Oregon State University

University of Washington

Ecological Sciences Need Better Instruments

- Scientific Questions:
  - How do communities of organisms interact?
  - Why does increased biodiversity create more resilient ecosystems?
  - How do invasive species succeed? How can they be stopped?

- Instrumentation Requirements:
  - What is the temporal and spatial distribution of organisms?
  - What is the population size of each species in a region?
  - What are all of the interactions (e.g., eating, mating) between pairs of organisms?

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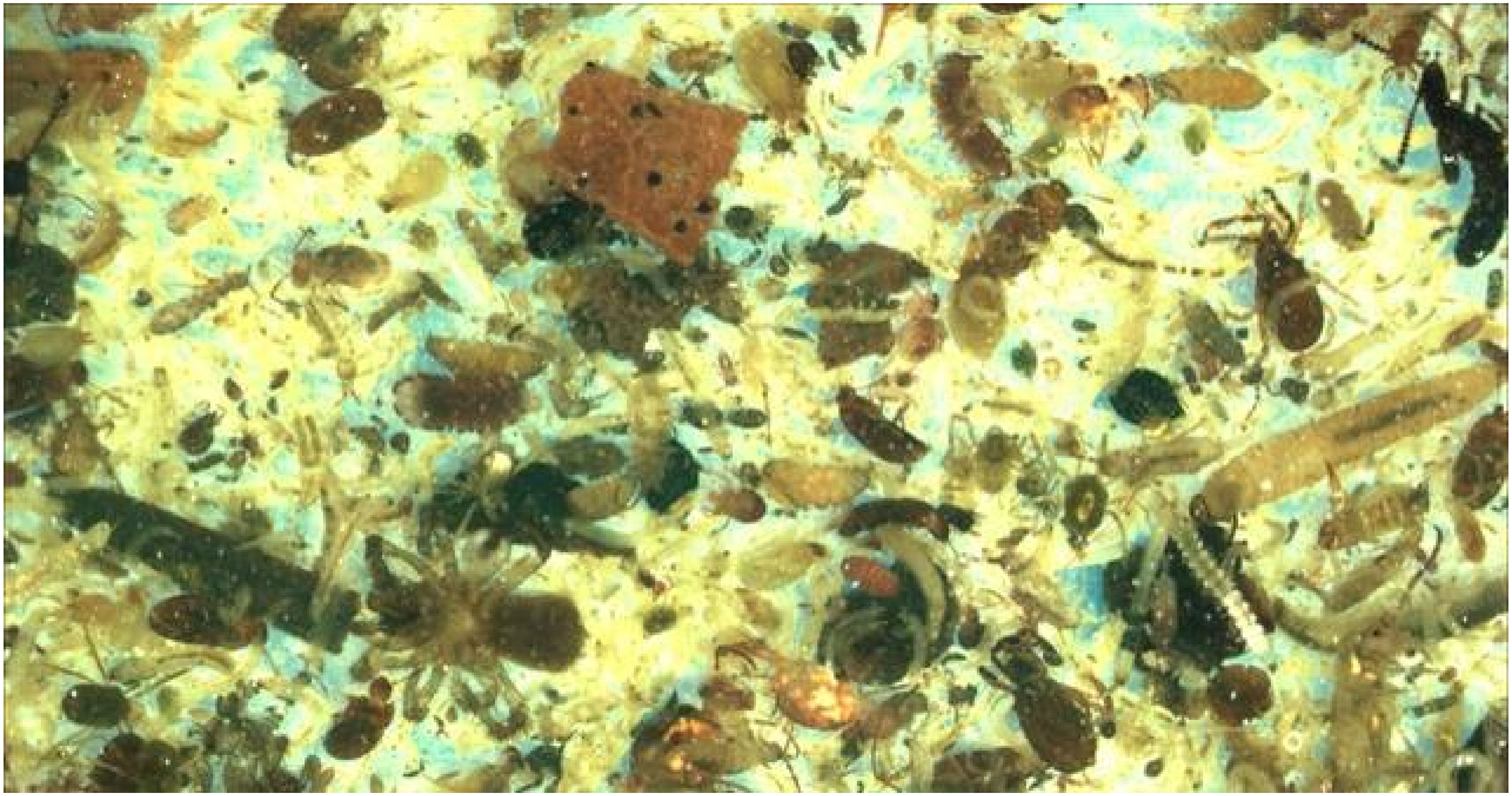
Example 1: Stonefly populations in freshwater streams

- differentially sensitive to many pollutants
- live in river substrate – reliable indicator of stream health
- difficult and expensive for people to classify (particularly to genus or species levels)

Example 2: Small arthropods in soil "soil mesofauna"



Soil Arthropods

- Measure biodiversity of soils
  - response of soil biodiversity to
    - forest/agricultural practices
    - disease
    - climate change
- ~2000 possible species

  ~100 species in any single sample

Goal: Rapid-Throughput Automated Arthropod Population Counting

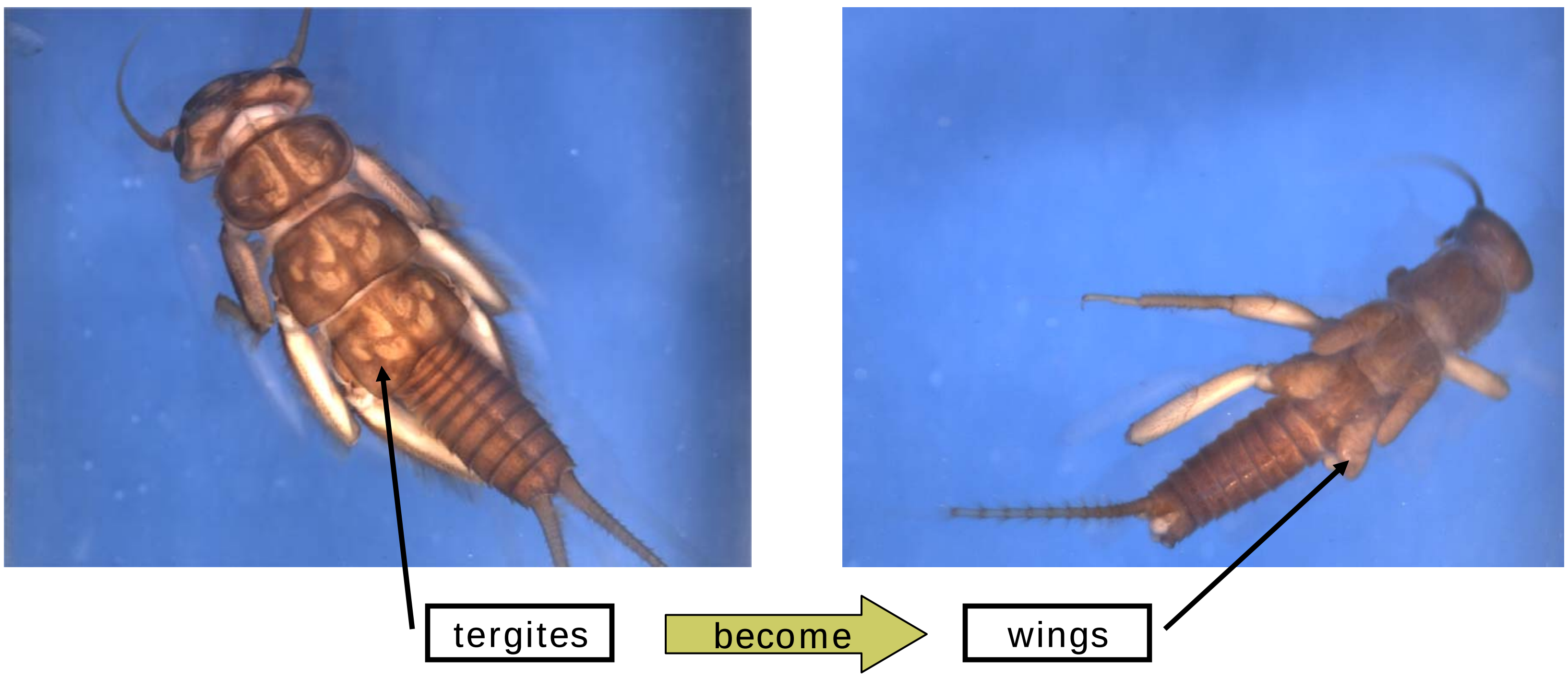
- Specimens are manually collected in the field following standard protocols
- Automated (robotic) devices photograph the specimens
- Images are then classified to family, genus, or species level

Computer Vision Challenges(1)

- Highly-articulated objects with deformation

Computer Vision Challenges(2)

- Huge intra-class changes of appearances due to development and maturation



Computer Vision Challenges(3)

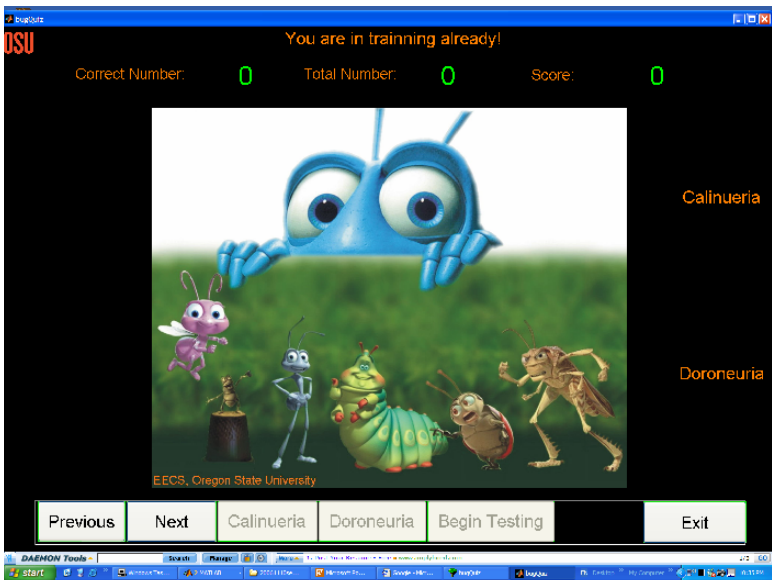
- Small between-class differences

Calinueria

Doronueria

Human Test

- Identifying them (from whole-specimen images) is hard even for humans



For Calinueria vs. Doronueria:

Mean Classification accuracy:

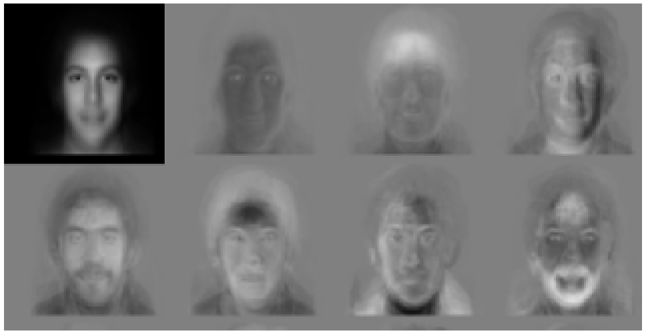
78.6%

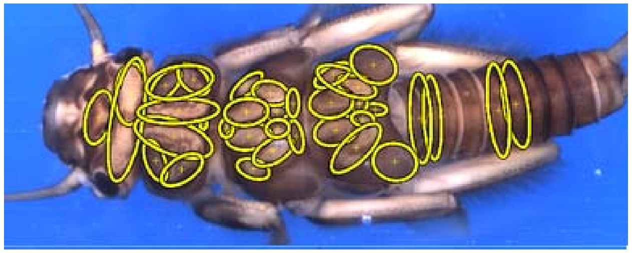
Standard Deviation:

8.4

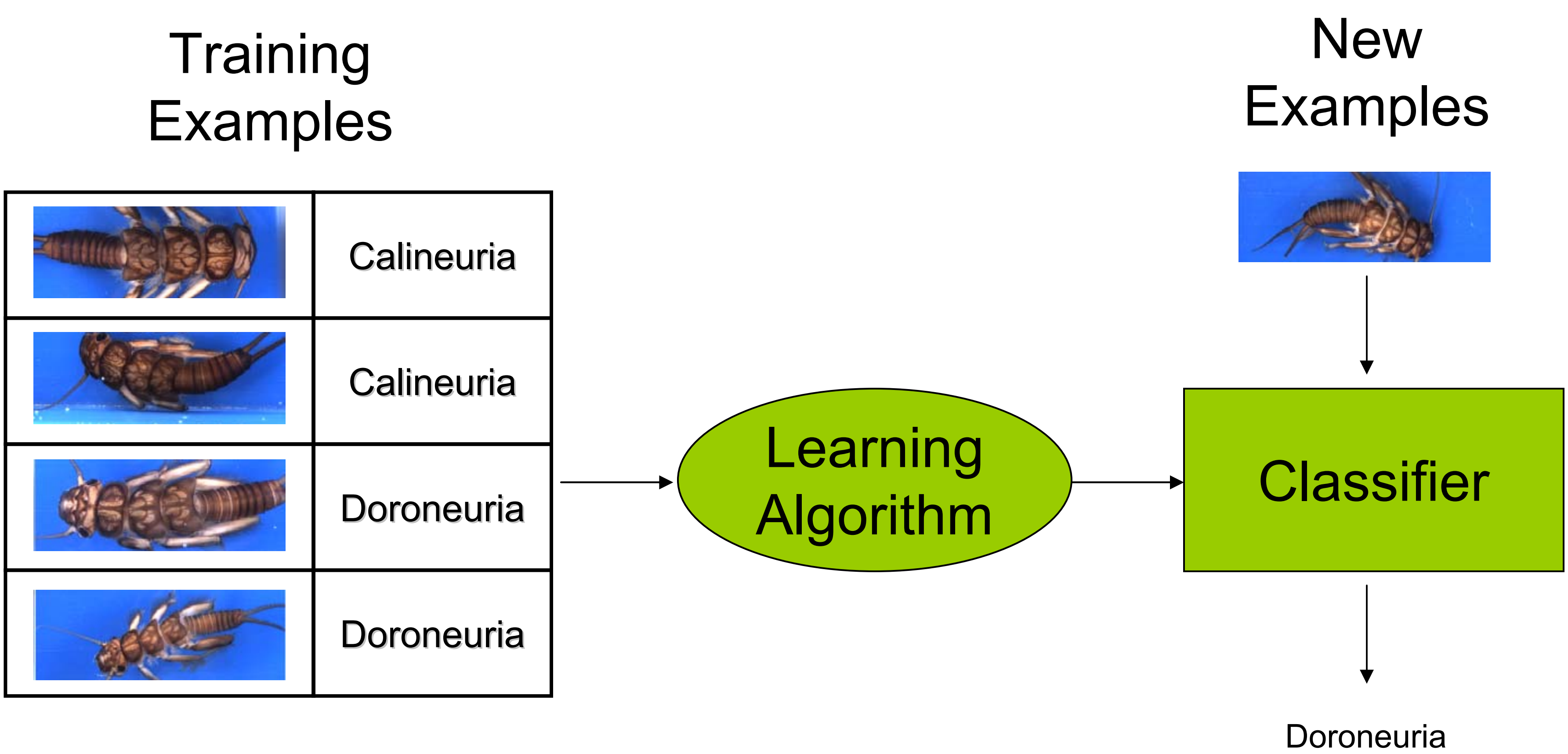
Modern Computer Vision Approaches

- Image based methods
  - Assumes objects are aligned across all images
  - Eigenfaces
- Model based
  - “inverse graphics”: parameterized model that can generate a predicted image
  - adjust parameters to obtain best match with the actual image
  - computation is very slow and expensive
- Patch based
  - identify “interesting regions”
  - extract and describe these regions
  - learn to recognize based on these regions





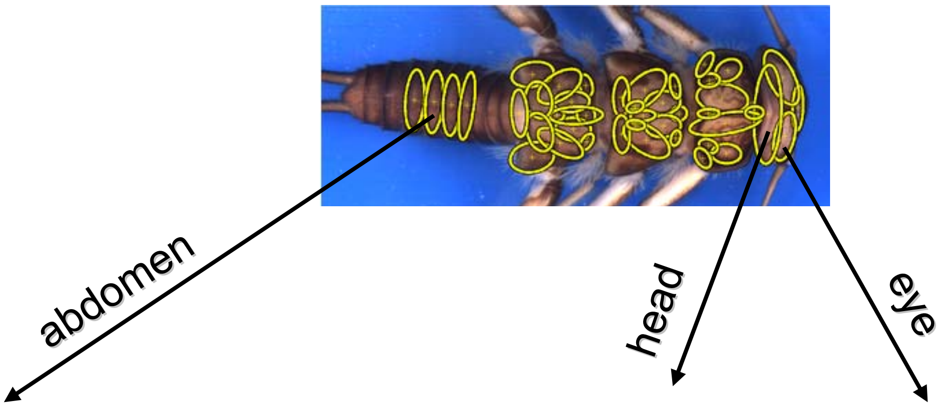
Machine Learning



Machine Learning Requires Fixed Number of "Features"

- To apply machine learning algorithms, we need to convert the image of a bug into a fixed number of "features"
- Idea: Create a "visual dictionary" of "parts" and then count parts

Count each detected "part" into a "feature table"

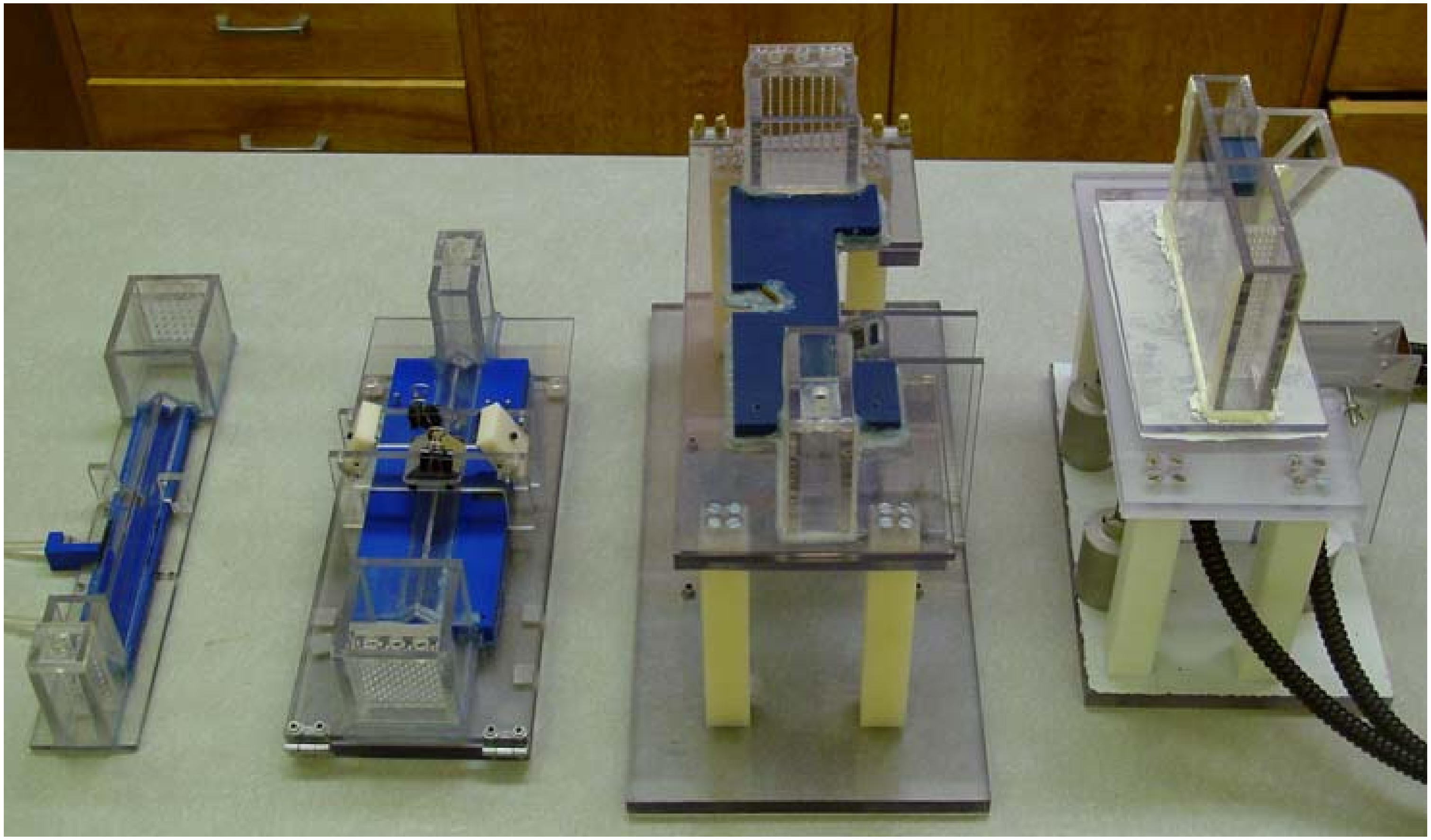


4	2	0	4	2	5	.	.	.	.	.	1	.	.	.	2	1	2		

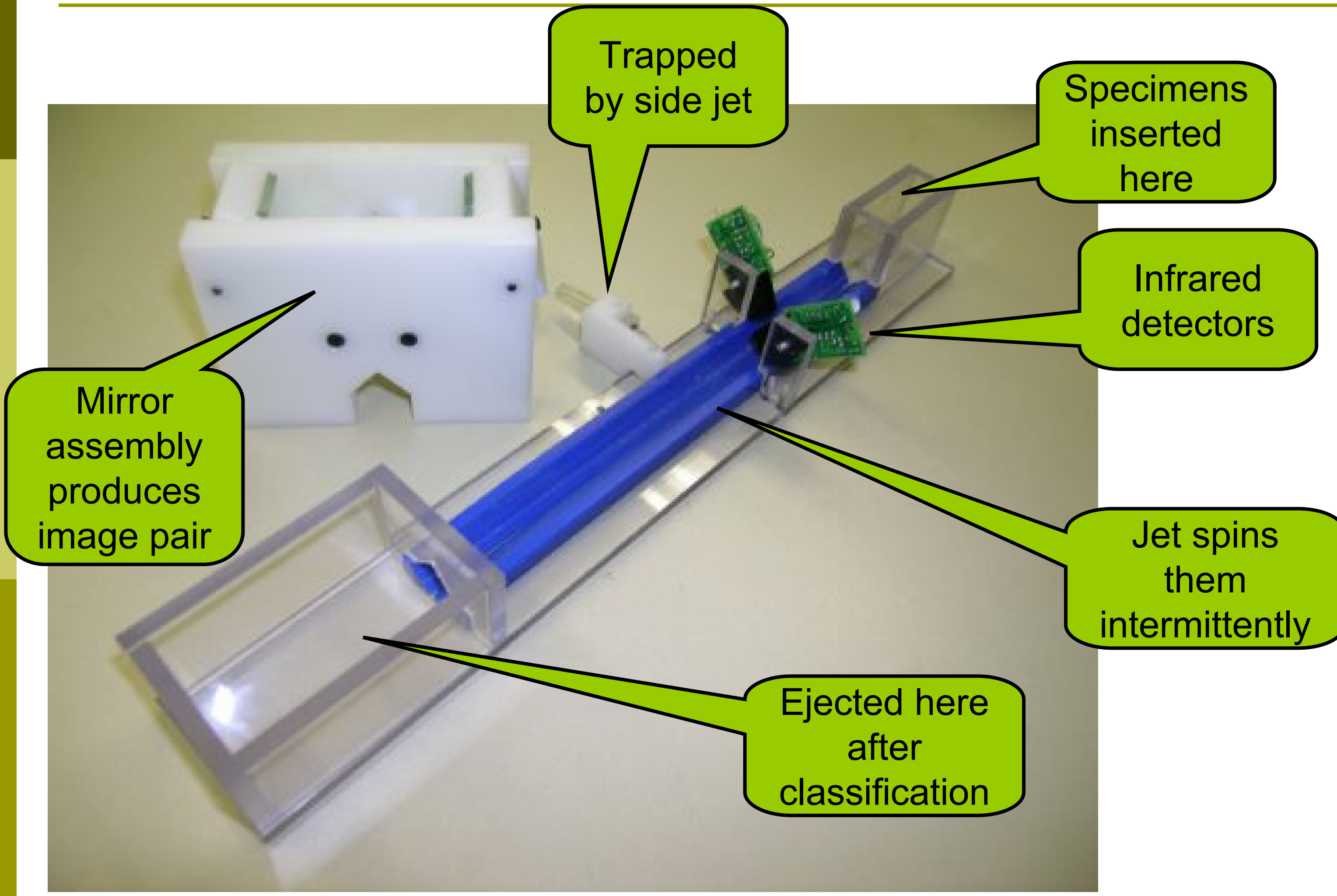
Stonefly Identification System

- Semi-automated specimen handling and photography
- Computer Steps:
  1. Dorsal view detection (not yet implemented)
  2. Region detection
  3. Region description
  4. Region mapping into features
  5. Combination into a “feature table”
  6. Classification

Semi-Automated Specimen Handling

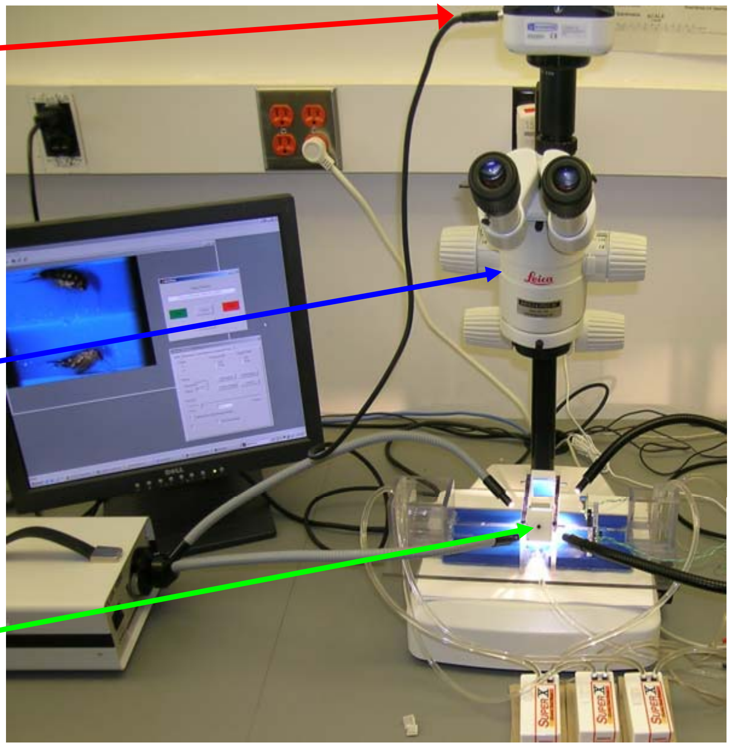


Semi-Automated Specimen Handling (2)

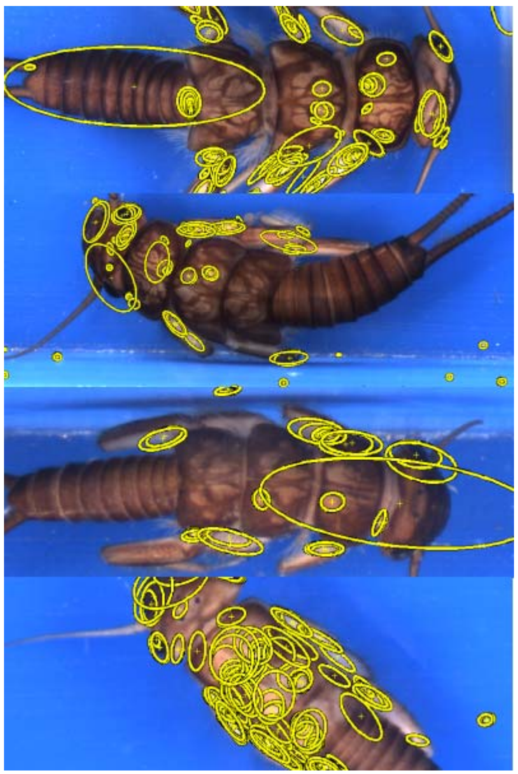


Semi-Automated Specimen Handling (3)

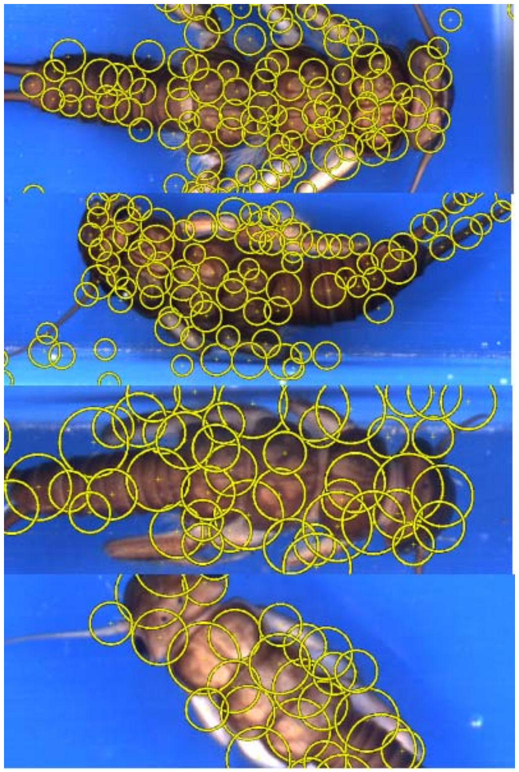
- Photographed by a 5 megapixel QImaging camera
- Leica microscope at 0.63x magnification
- Mirrors capture two views per image



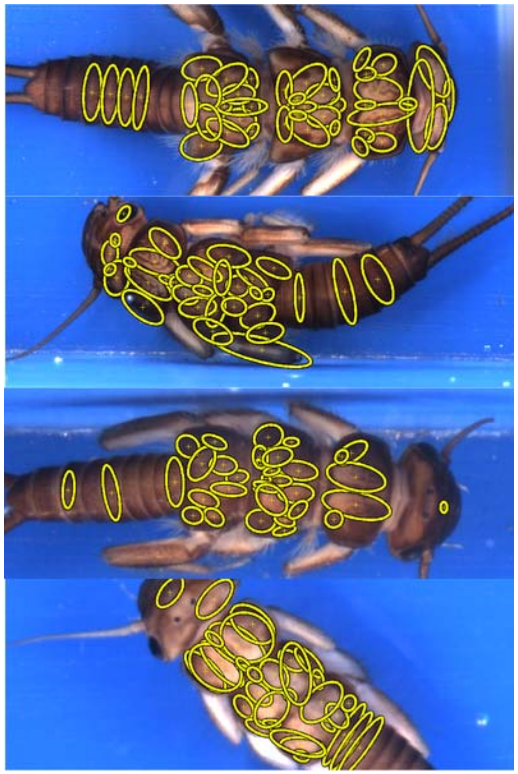
Region Detectors



Hessian-Affine Detector

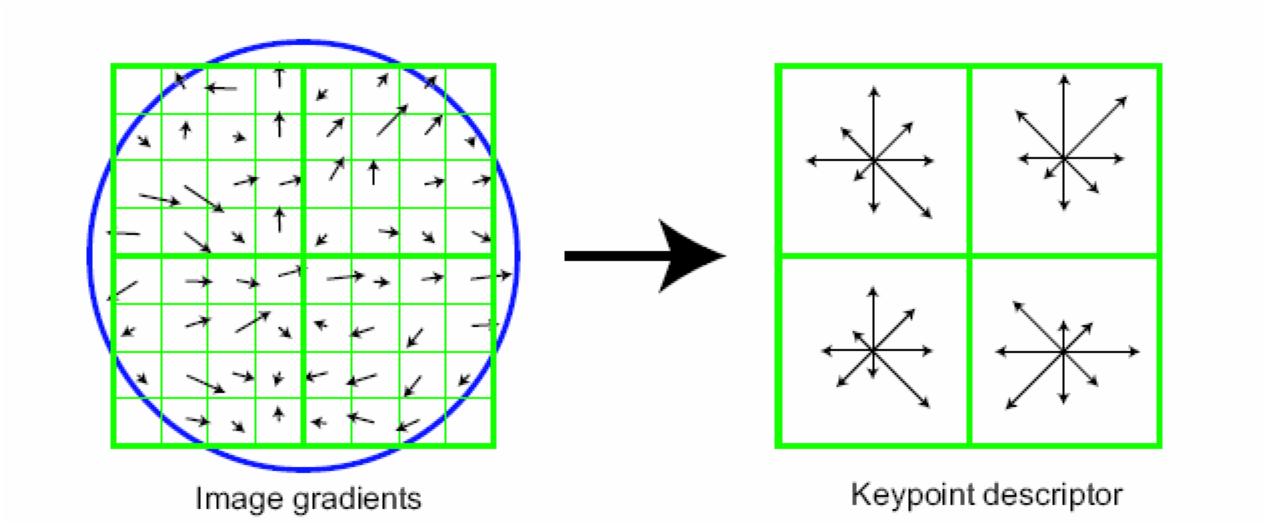


Kadir Entropy Detector



PCBR Detector

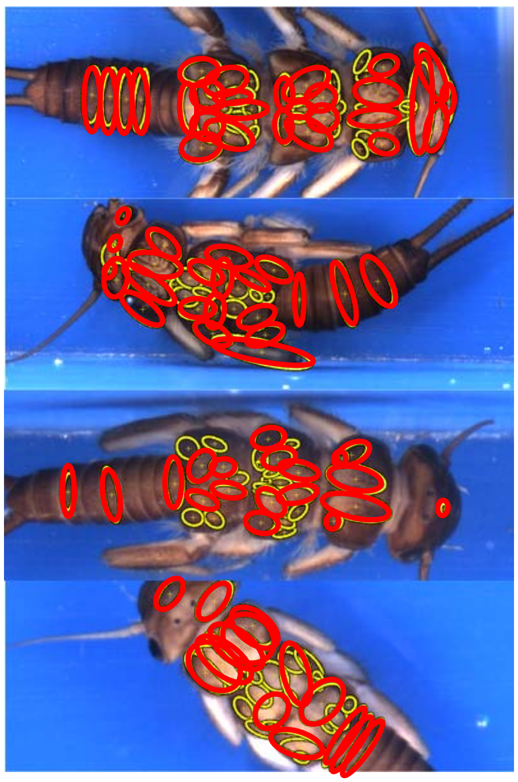
Scale-Independent Feature Transform
SIFT (Lowe, 1999)

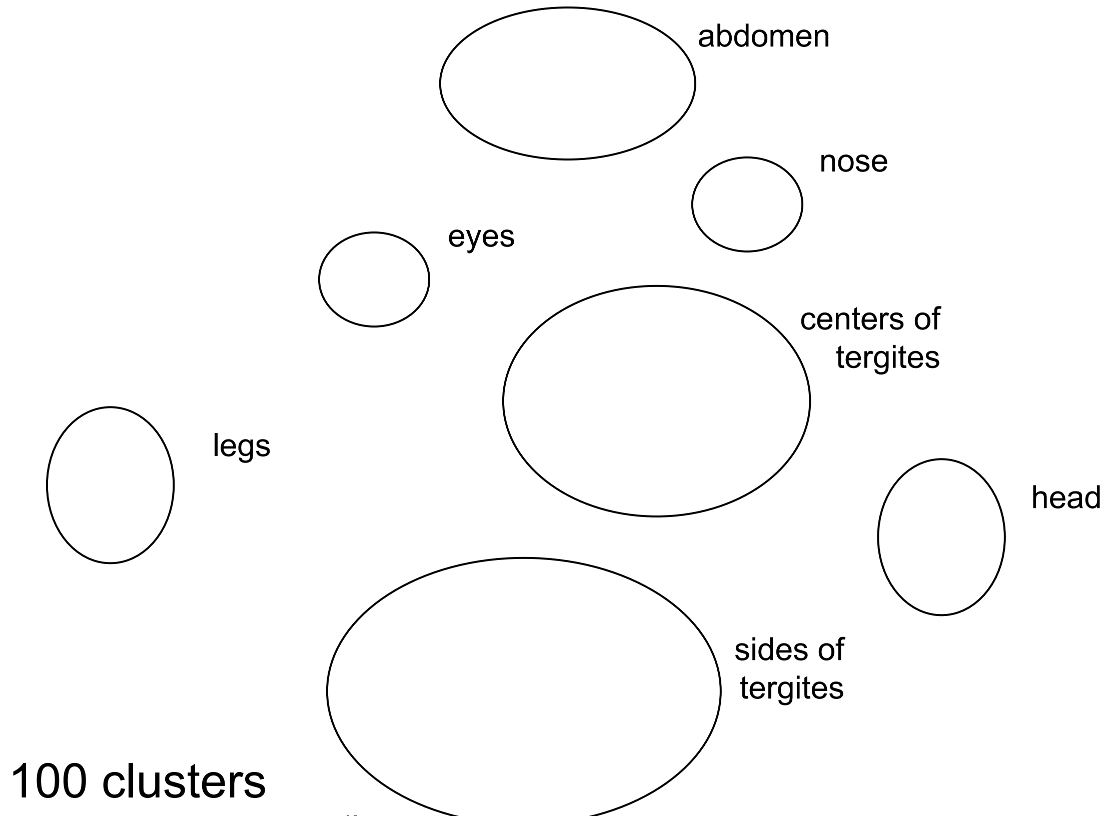


- Compute intensity gradient at each pixel in 16x16 region
- Weight them by a gaussian distribution (indicated by circle)
- Collect into histograms within each 4x4 region (gives 16 histograms)
- Result: 128-element vector normalized to have Euclidean norm 1

Cluster Analysis of the SIFTs

- Automatically group together similar regions to build a "visual dictionary" for each species





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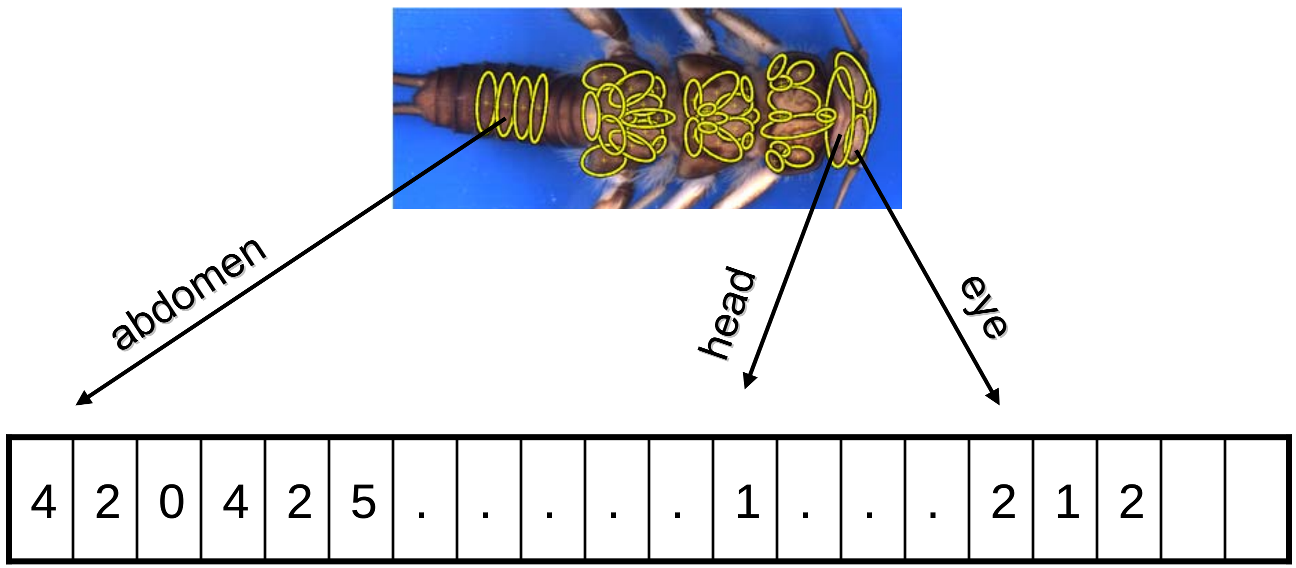
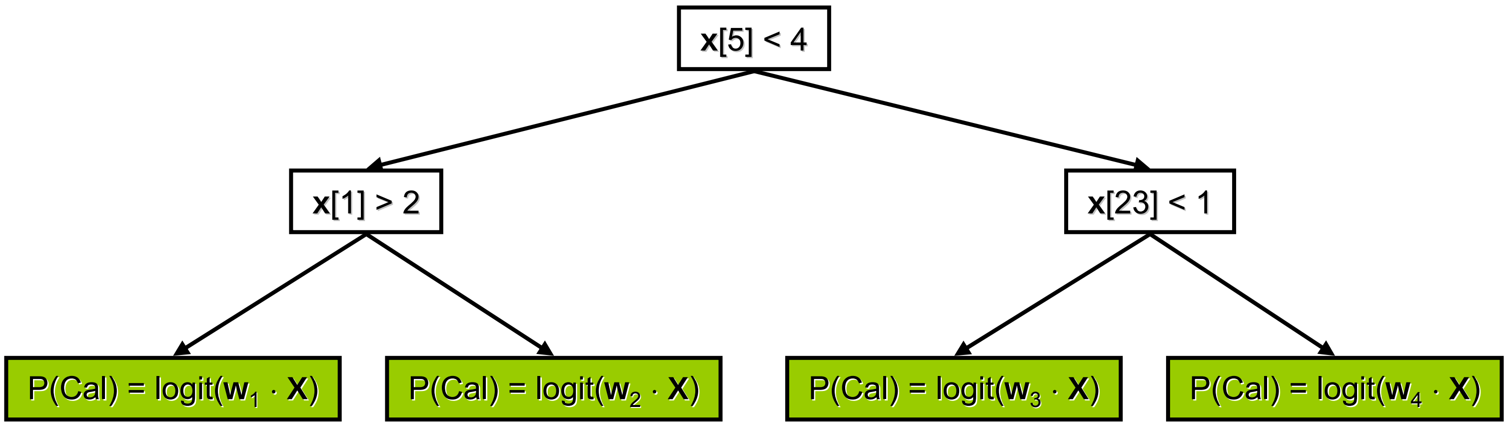
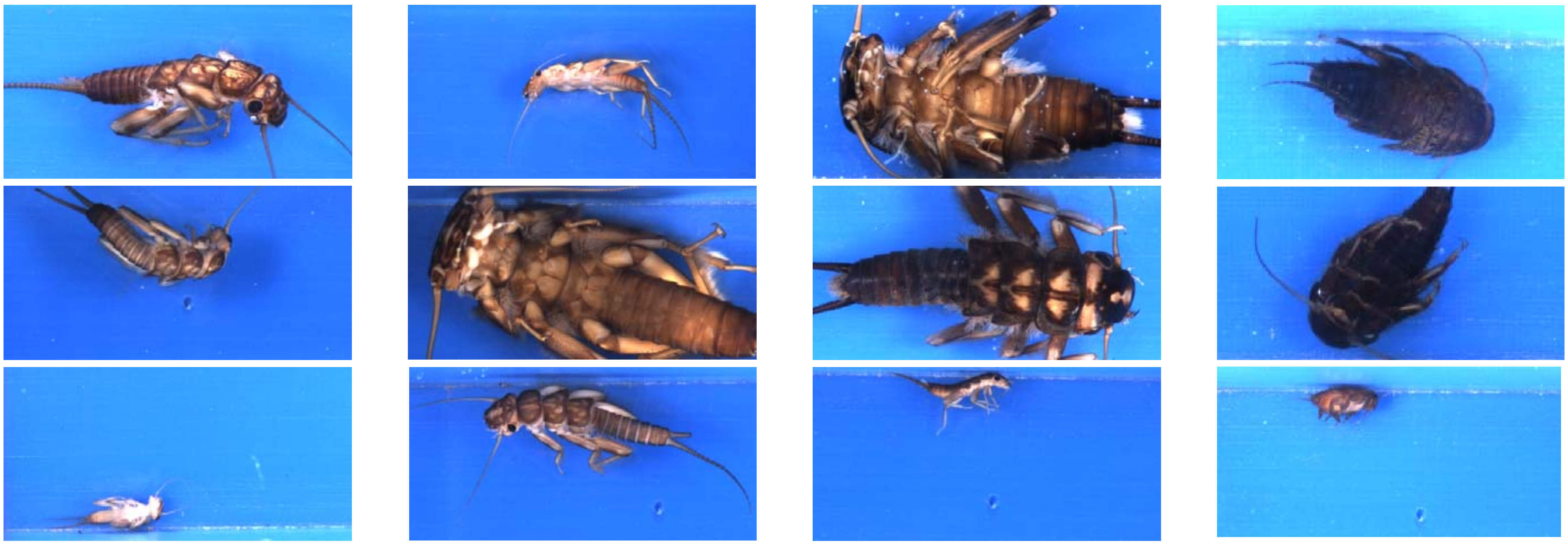


Learning Algorithm

- Bagged Logistic Model Trees



Experimental Study



Calineuria | Doroneuria | Hesperoperla | Yoroperla

Experiment Design

- Data set

Taxon	Specimens	Images
Calineuria	85	400
Doroneuria	91	463
Hesperoperla	58	253
Yoraperla	29	124

- Split into 3 parts by specimens, balanced by taxon
  - clustering
  - training
  - testing

Results

- Overall accuracy: 82.42% (±2.14)
- Confusion matrix

		Predicted Class			
		Cal.	Dor.	Hes.	Yor.
True Class	Calineuria	313	81	6	0
	Doroneuria	87	374	2	0
	Hesperoperla	24	19	206	4
	Yoroperla	1	0	0	123

Discussion

- Discriminating Cal. vs. Dor. is very difficult
  - Human study: 26 students and faculty from OSU Entomology program
    - trained on 50 Cal and Dor images
    - tested on 50 Cal and Dor images
    - 78.6% correct
  - Comparison:
    - our system trained only on Cal. Vs. Dor. is 79.37% correct ($\pm$2.70)
  - If we combine the Cal. and Dor. classes, then our system is 95.40% correct ($\pm$1.20)

Why Three Region Detectors?

- The combination of all three gave better results than any other configuration:

Hessian Affine	Kadir Entropy	PCBR	Accuracy
√			73.14
	√		70.64
		√	71.69
√	√		78.14
√		√	80.48
	√	√	78.31
√	√	√	82.42

The Same Method Works On Other Tasks

- Caltech 2-class data sets

Dataset	IDC-BDL	Fergus (IJCV 2007)	Opelt (PAMI 2006)	Dorko (RR5497 2005)	Chen (PAMI 2006)
Airplanes	**99.2**	93.7	88.9	98.8	98.0
Faces	98.4	91.7	93.5	**99.5**	**99.5**
Motorbikes	98.3	96.7	92.2	**99.5**	96.7
Leopards	**98.0**	89.0		91.0	
Cars (Rear)	**95.5**	91.2	91.1		94.5

- UIUC cars versus no-car background

Dataset	IDC-BDL	Fergus (IJCV 2007)	Opelt (PAMI 2006)
Cars (Side)	**92.7**	88.5	83.0

Other Datasets (2)

- GRAZ-01 2-class problems

Dataset	IDC-BDL	Opelt (PAMI 2006)
Bikes	**76.5**	73.5
Persons	**71.7**	63.0

New Results: 9 Stonefly Taxa

- Classifier Adaboost M1
  - 65 Iterations
  - Base Classifier: Pruned C4.5 trees

					Acc:	**3269**		**85.6%**			
					Tot:	**3821**					
Classified as ==>			a	b	c	d	e	f	g	h	i
Cal	=	a	75.61	12.60	0.41	7.11	0.41	0.61	0.81	0.00	2.44
Dor	=	b	12.41	79.51	2.63	4.70	0.00	0.00	0.75	0.00	0.00
Hes	=	c	1.22	3.87	92.46	0.41	0.00	0.61	1.22	0.00	0.20
Iso	=	d	3.00	1.60	0.20	89.60	0.40	0.00	3.40	0.00	1.80
Mos	=	e	5.22	2.61	0.87	2.61	49.57	3.48	3.48	1.74	30.43
Pte	=	f	0.00	0.90	4.05	0.45	0.45	73.42	6.76	4.05	9.91
Swe	=	g	2.71	1.04	0.21	5.01	0.42	1.25	86.01	1.88	1.46
Yor	=	h	0.00	0.00	0.00	0.20	0.20	0.61	2.64	93.09	3.25
Zap	=	i	1.20	0.00	0.20	0.60	0.20	1.20	1.41	3.21	91.97

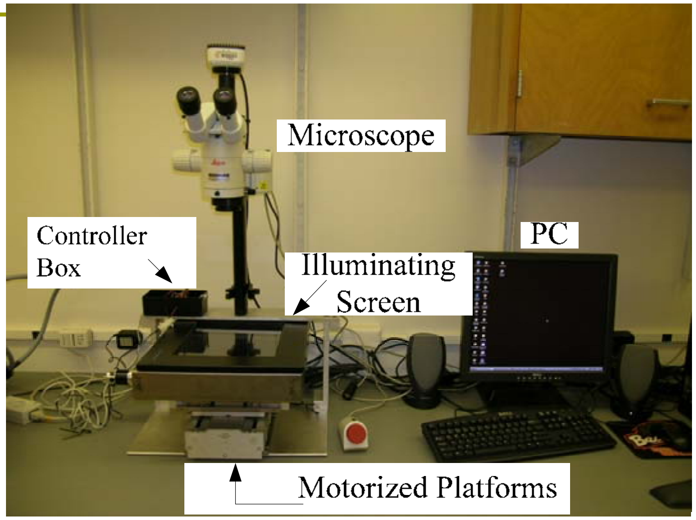
Future Work

- Dorsal view detector
- Mechanical sorting on the output
- Reject unknown species

- Propose field testing to EPA
- License for commercialization

Soil Mesofauna

- ~2000 species possible, but only ~100 in any given sample
- motorized X-Y stage and focus
- step focus through 12 levels and combine to produce high depth-of-field synthetic image
- vary background lighting to compute transparency
- employ shape in addition to appearance
- robot arm with pipette will extract each identified specimen and place in 96-well plate



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