Stabilizing Novel Objects by Learning to Predict Tactile Slip

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Qualification Exam Presentation

May 27, 2022

Self Introduction

- 2007 BS Mathematics, UIUC
- 2020 MS Mechanical Engineering, UIUC
  - Thesis: *Investigating Pre-touch Sensing to Predict Grip Success in Compliant Grippers Using Machine Learning Techniques*

- Research interests:
  - Manipulation and grasping
  - Agricultural robotics
  - Gripper design
- Other interests
  - Mechatronics
  - Legged Locomotion

Course Work

- ME 445 Introduction to Robotics
- ME 446 Robot Dynamics and Control
- ECE 486 Control Systems
- ME 540 Control System Theory and Design
- ECE 517 Nonlinear & Adaptive Control
- ECE 534 Random Processes
- ME 498 Bioinspired Design
- TAM 412 Intermediate Dynamics
- ECE 448 Artificial Intelligence

Projects

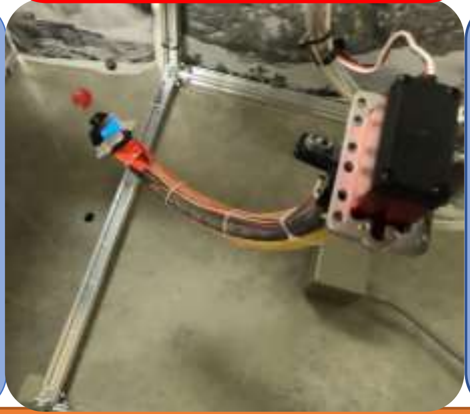
Stretchable fiber optic sensors

Gripper design for berry picking

Pre-touch sensing to predict grip success

System integration of a VaLeNS arm on a mobile platform

Visual servoing with a gantry mounted BR2 arm



Development of a dynamic controller for the VaLeNS arm (In progress)

Slip detection in agricultural work (In progress)

- N. K. Uppalapati, **B. T. Walt**, A. Havens, A. Mahdian, G. Chowdhary, and G. Krishnan, "A Berry Picking Robot With A Hybrid Soft-Rigid Arm: Design and Task Space Control," in Robotics: Science and Systems Foundation, 2020.
- S. K. Kamtikar, S. Marri, **B. T. Walt**, N. K. Uppalapati, G. Krishnan, and G. Chowdhary, "Visual Servoing for Pose Control of Soft Continuum Arm in a Structured Environment," in IEEE Robotics and Automation Letters, 2022.

Presentation Overview

- Brief introduction of the paper
- Background of slip prediction and detection
- Walkthrough of the paper
- Discussion of the paper
- My research and connection to the paper

Stabilizing Novel Objects by Learning to Predict Tactile Slip

Filipe Veiga, Herke van Hoof, Jan Peters, Tucker Hermans

2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)

Brief overview of the paper

This paper uses a bio-inspired tactile sensor to determine when an object is slipping or about to slip and then takes action to prevent further slip.

To help create a generalizable approach, machine learning is used to determine the slip state.

The results are applied to a simple controller to demonstrate its effectiveness

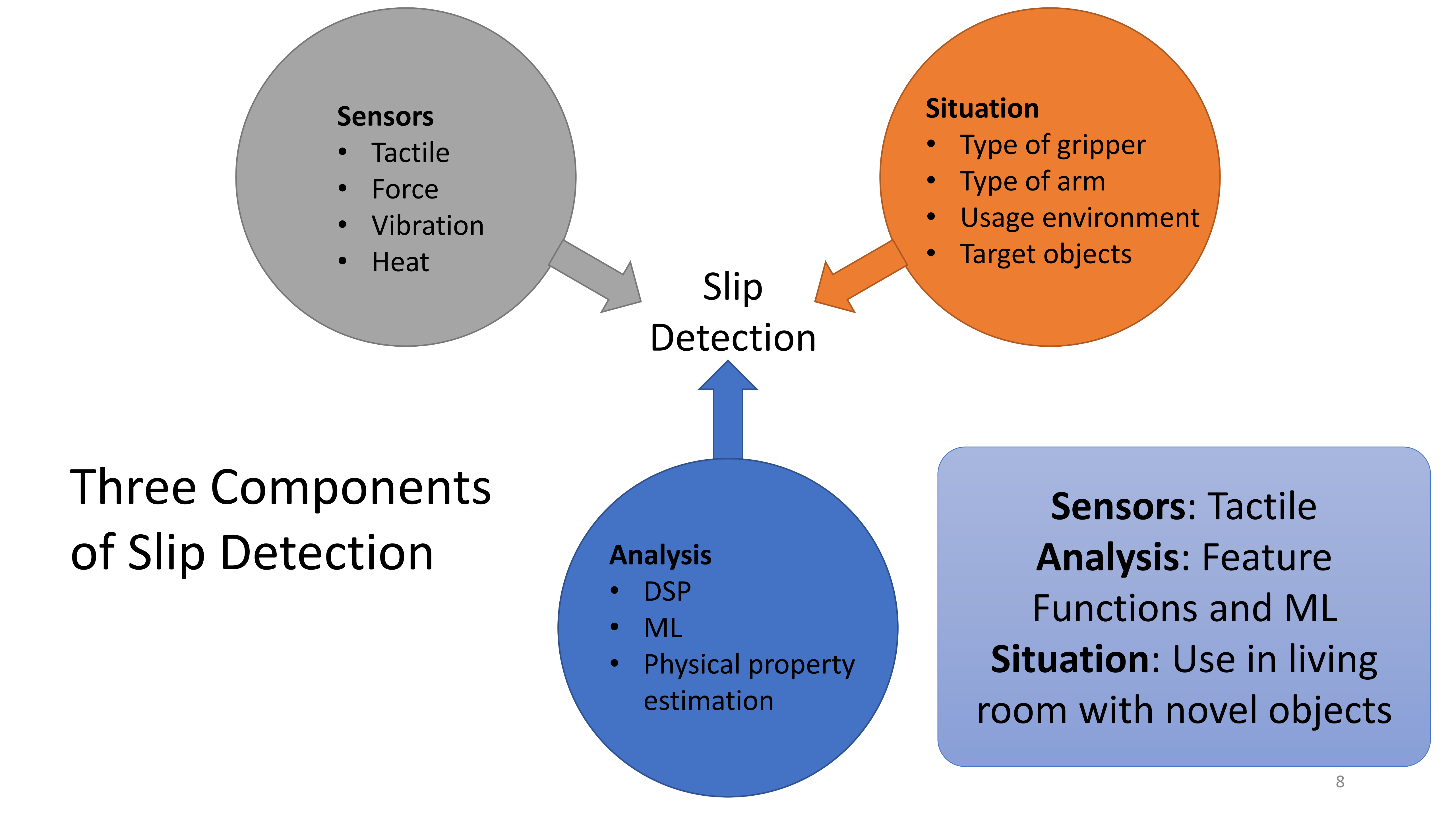
Background of Slip

Grasp stability – the ability to maintain the pose of the grasped object despite disturbances

Incipient slip – Some contact points shift or lose contact. This is a precursor to *gross slip*

Gross slip – All contact points shift or lose contact and cause the grasped object to change pose

Grasp failure – *Gross slip* to the point that the grasped object leaves the gripper entirely


Sensors
• Tactile
• Force
• Vibration
• Heat
Situation
• Type of gripper
• Type of arm
• Usage environment
• Target objects
Slip Detection
Analysis
• DSP
• ML
• Physical property estimation
Three Components of Slip Detection
Sensors: Tactile
Analysis: Feature Functions and ML
Situation: Use in living room with novel objects
8

Paper Structure

- Introduction
- Related Work
- Learning to Predict Slip
  - Explanation of the feature functions and ML methods
- Stability Control Using Slip Prediction
  - Explanation of the stabilization method
- Experimental Evaluation
  - Experimental Setup
  - Description and analysis of results
- Conclusion and Future Work

Contributions

Primary

A generalizable method of slip prediction using a tactile sensor which can be used to stabilize a previously unknown object.

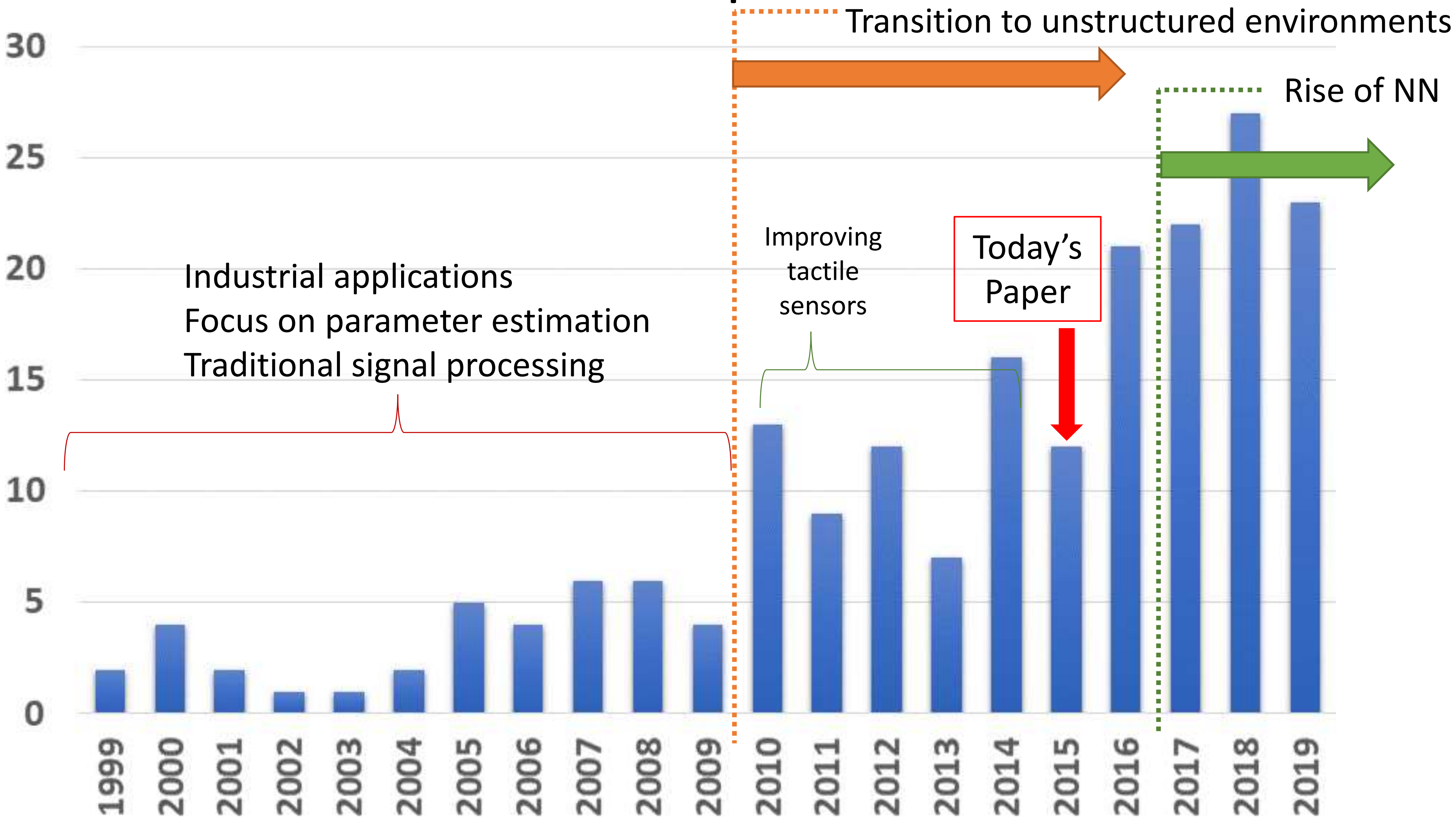
Secondary

- Two common ML methods (SVM and Random Forests) were evaluated for their effectiveness in slip detection and prediction.
- A large number of feature functions were tested and analyzed to find the best choices and to better understand why they work.

Related Work - Timeline of Slip Detection

Earlier works

- **1967** – A mechanical hand with automatic proportional control of prehension
- **1993** - Estimating Friction Using Incipient Slip Sensing During a Manipulation Task
- **1998** - Detection of incipient object slippage by skin-like sensing and neural network processing



Number of scientific publications each year with keyword 'robot slip sensor'

Related Work – Key background papers

Using robotic exploratory procedures to learn the meaning of haptic adjectives (2013)
- Feature functions
- Chu et al. in the paper

Human-Inspired Robotic Grasp Control With Tactile Sensing (2011)
- Developed a similar stabilization scheme

Multimodal Tactile Sensor (2014)
- Walkthrough of the BioTac sensor by the creators

Experimental Comparison of Slip Detection Strategies by Tactile Sensing with the BioTac on the DLR Hand Arm System (2014)
- Uses random forests

Learning to Predict Slip

Collect tactile data with the BioTac sensor

Extract features from this data with a feature function: $\varphi(\cdot)$

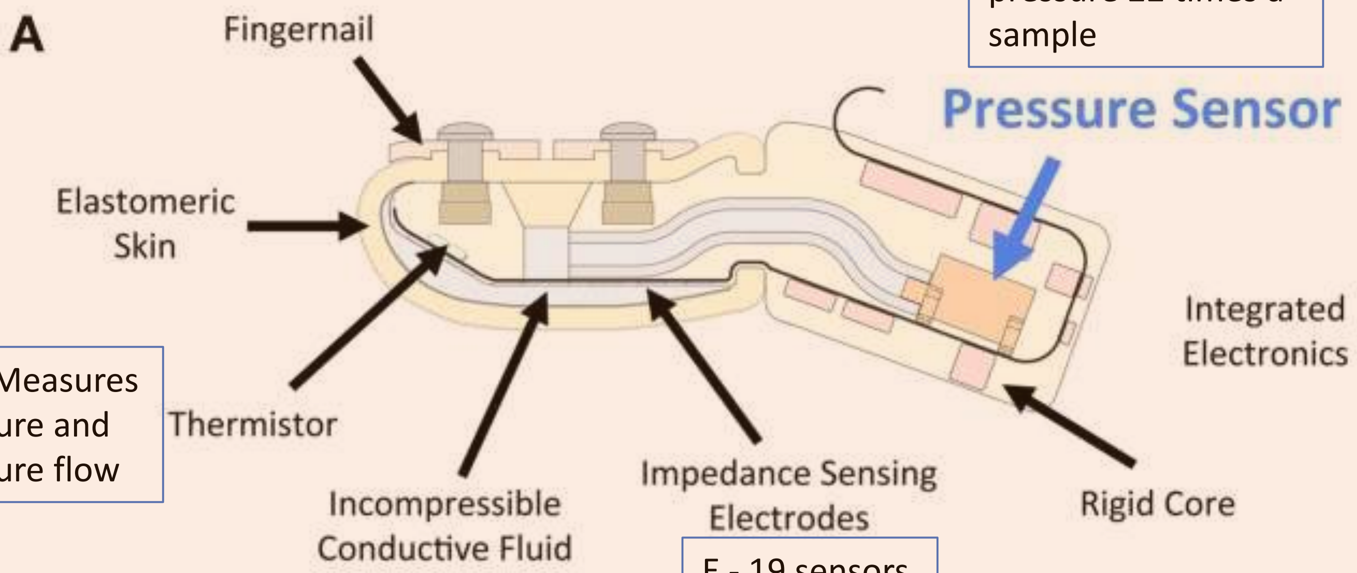
Find a function, $f(\cdot)$, such that $c_t = f\big(\varphi(x_{1:t})\big)$ where $c_t \in \{c_{slip}, c_{non-slip}\}$
(ML Techniques)

F_{score} is used as the evaluation metric

Slip prediction is explored by adding a positive time step: τ_f
$c_{t+\tau_f} = f\big(\varphi(x_{1:t})\big)$ e.g. $c_{200} = f\big(\varphi(x_{1:190})\big)$

Overview of BioTac Sensor

P_{DC} & P_{AC} - Measures pressure 22 times a sample



T_{DC} & T_{AC} Measures temperature and temperature flow

E - 19 sensors for localized pressure

- Biomimetic sensor to simulate a fingertip's sense of touch
- 3 kinds of sensors (44 data points per sample reading):
- Can be read at 100Hz

Feature Functions

Single element feature function

$\varphi(x_{1:t}) = x_t$

Delta feature function

$\varphi(x_{1:t}) = [x_t, \Delta x_t]$

Time window feature function

$\varphi(x_{1:t}) = x_{t-\tau:t}$

τ is the size of the time window of past data

Chu et al. feature functions

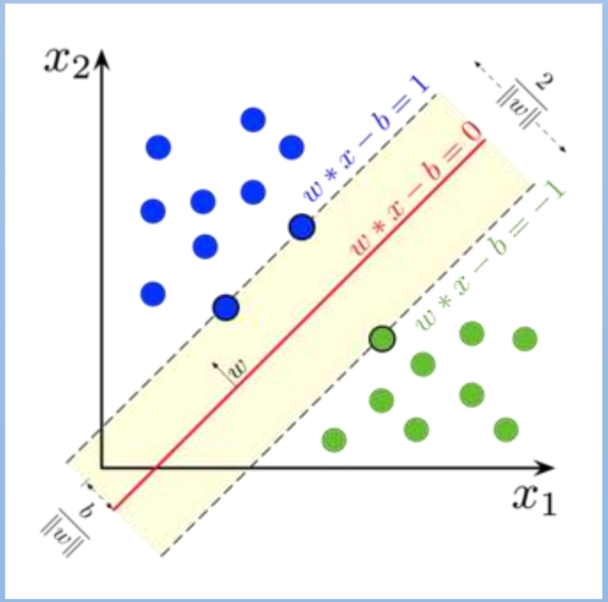
This is a collection of features developed for tactile sensing of object properties

Classification

Support Vector Machine

Separates categorical data with a hyperplane

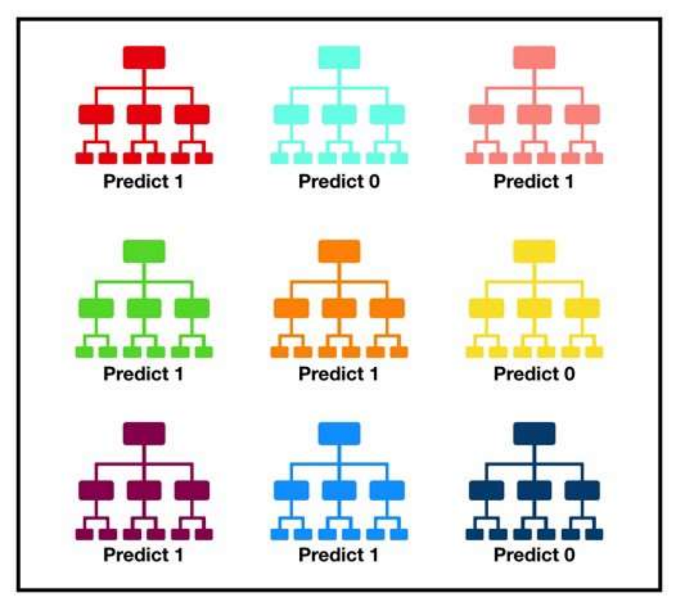
- Works well with large feature sets
- Works with smaller data sets
- Lacks interpretability
- Affected by noise



Random Forest

Uses the power of consensus to classify data

- Works well with large feature sets
- Robust to outliers
- Rejects noise well
- Lacks interpretability
- Complex to train



Accuracy Evaluation

F_{score}

F_{score} is selected as it balances **precision** and **recall**

- The harmonic mean of the two

$$F_{score} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Precision

Precision represents how well it labels positives (slip) correctly

- A high precision means it rarely labels non-slip as slip

$$\text{precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

Recall

Recall represents the ability to identify the positives (slip)

- A high recall means it labels slip as slip well

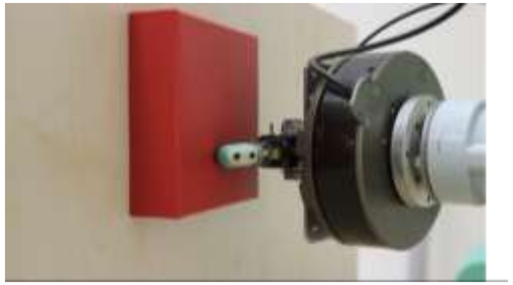
$$\text{recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Stability Control Using Slip Prediction

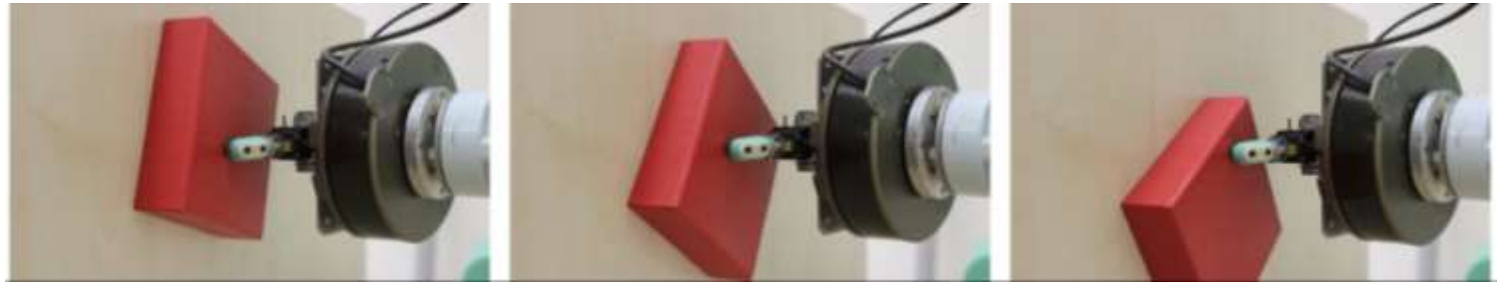
$$F_N[t+1] = \begin{cases} F_N[t] + \delta \hat{F}_N[t+1], & \text{if } c_t = c_{slip} \\ F_N[t], & \text{otherwise} \end{cases}$$

δ – a small scaler value
$\hat{F}_N$ - Unit normal

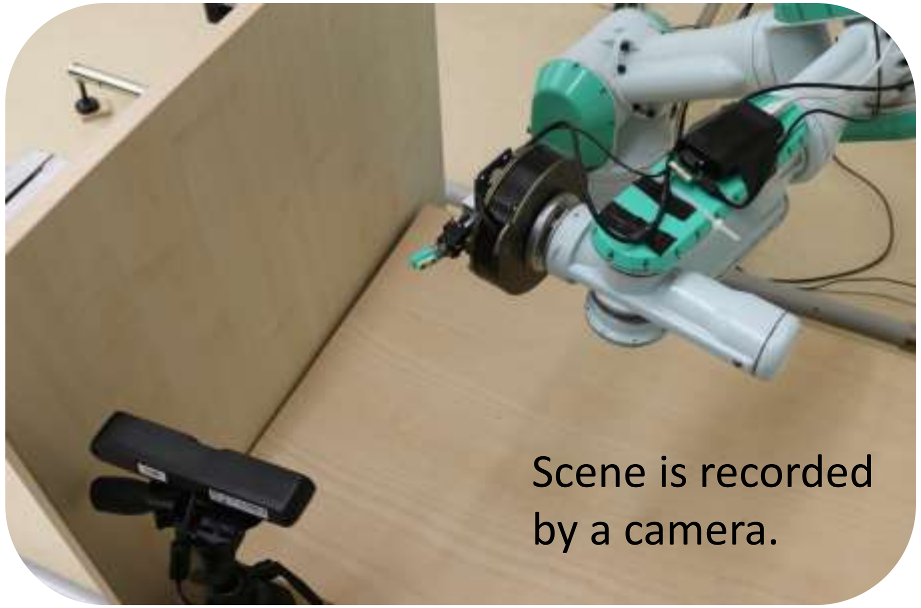
Experimental Evaluation - Experimental Setup



Object is pressed against the vertical surface by the BioTac finger.



The finger is moved away from the surface at a constant speed. Gross slip occurs.



Grasp failure occurs when object is no longer held.

Experimental Evaluation - Results

Slip Detection

- A classifier for each object
- A single classifier for all objects
- A single classifier for all objects – except one
- SVM vs Random Forest
- All Feature Functions
- Spectral Slip

Slip Prediction

- A classifier for each object
- A single classifier for all objects
- A single classifier for all objects – except one
- <u>Only Random Forest</u>
- <u>Single and Delta Feature Functions</u>
- Different τ_f for prediction

Stabilization

- A single classifier for all objects – except one (Generalization)
- Only Random Forest
- Single and Delta Feature Functions

Experimental Evaluation - Results

Slip Detection – Random Forest shows promise to generalize

- Results are generally strong, but depend on object properties
- Mean values are not significantly different.
- Little difference in 'per object' and 'all objects' classifiers.

Slip Prediction – Results similar to detection

- Best results are with τ_f =10 (Smallest time step)

Stabilization – Successful, but inconsistent results

- Results show a lot of successes, but they depend highly on the object

Object Characteristics

- **Easier**: Box and tape
- **Harder**: Ball and watering can

Conclusion

- They successfully created a slip detector that generalized well to new objects and were able to apply the detector to a controller that stabilized an unstable grasp
- Future Work
  - Measure other tactile events
    - making/breaking contact with object
    - making/breaking contact with support surface
  - Auto-labelling the data

Paper Discussion

My response

Detection vs Prediction

Feature Functions
(Chu's Feature Functions)

Data Overload

Exploration of role tactile signals play

Impact of the paper

Factory -> Living room

Generalization through ML

Implemented it on a real system

Tactile Sensing

Helped set the stage for the current trends in slip detection:

- ANN – especially RCNN/LSTM
- Sensor fusion - vision or other sensors
- Growth in visual-tactile sensing

Slip detection in an agricultural setting

My Current Research

Motivation

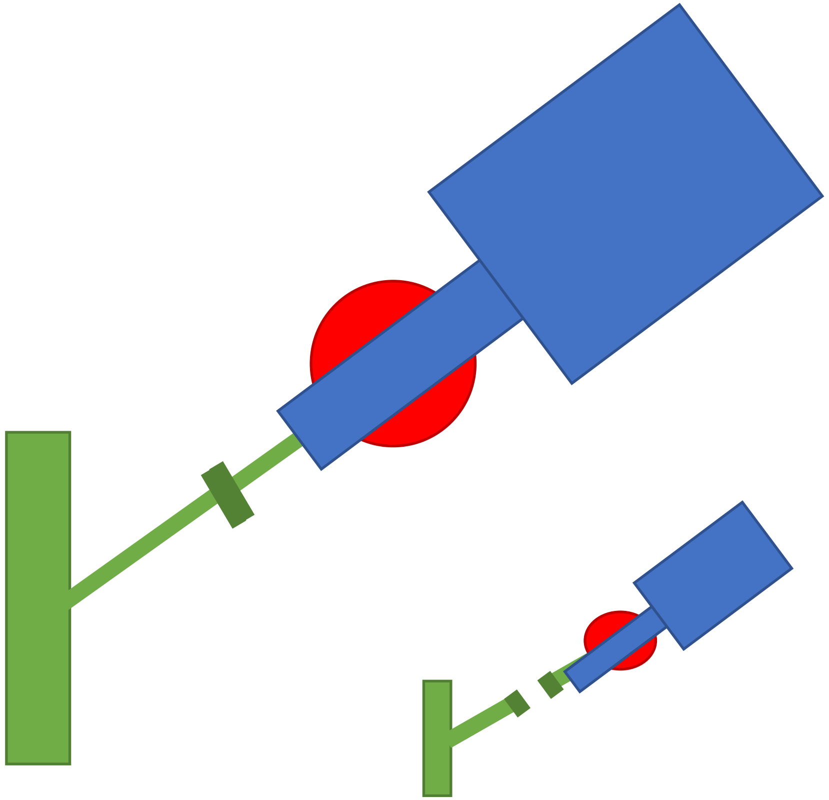
- *** Video Removed***
- Motivating video to show why slip detection in agriculture is important
- https://youtu.be/QsXXaIffZ78

Unique Fruit Picking Issues

- Fruit are often soft
- Some fruit are very smooth
- Grow in wet/dusty environments

- Environment is cluttered
- Complex plucking motions

- Fruit are attached to the plant
- Separation can be rather sudden



Goals

Generalizable to grippers that work in agriculture

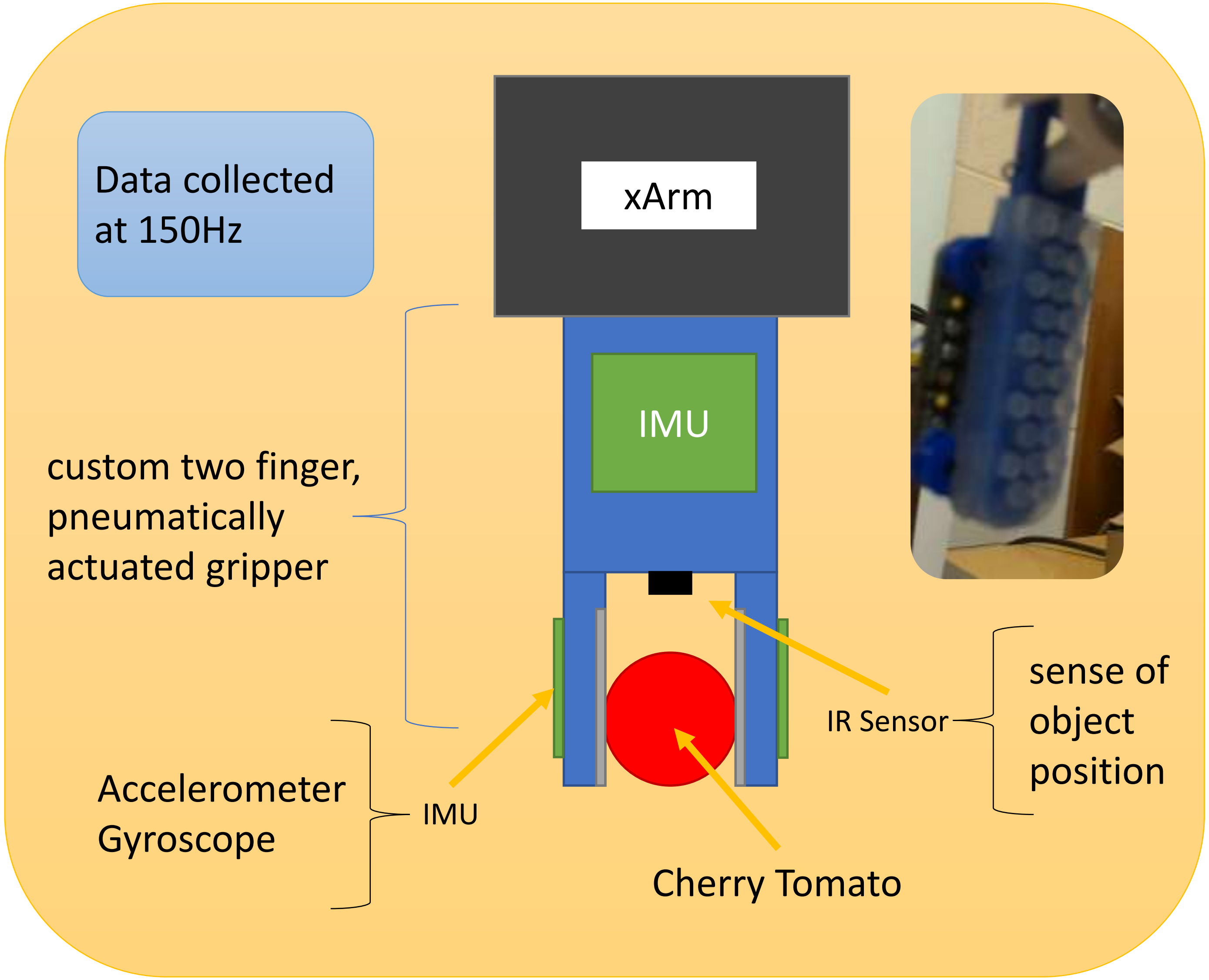
Able to function in the agricultural environment

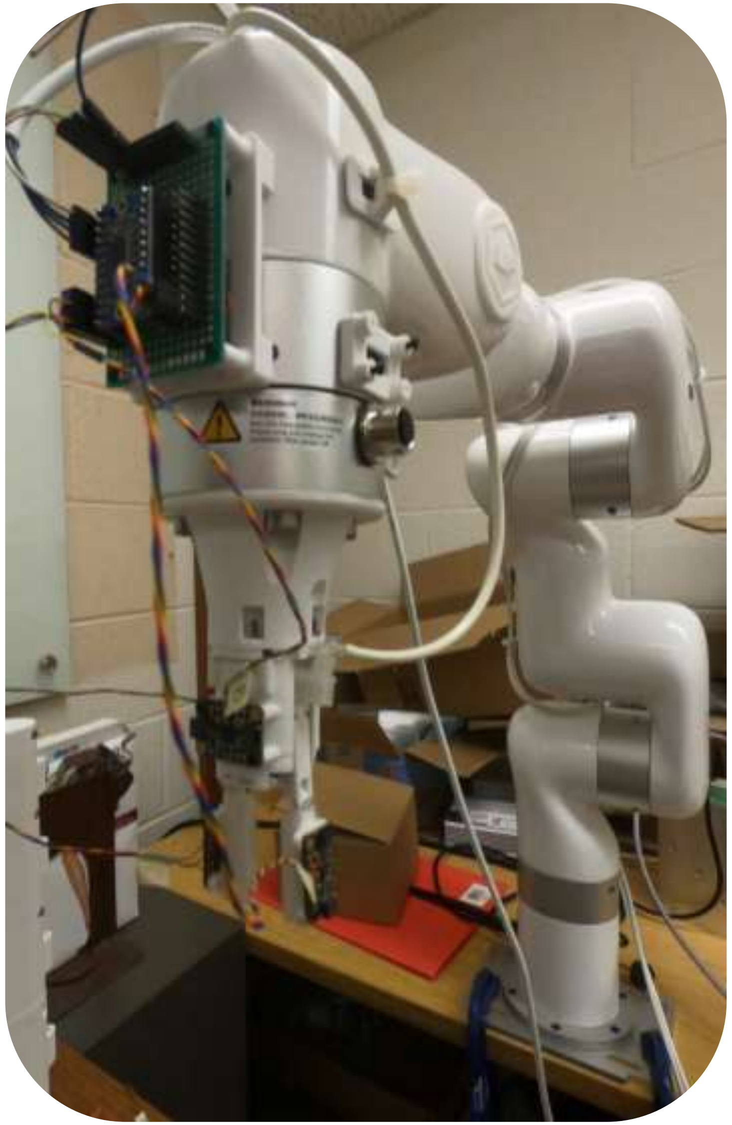
Can overcome the unique challenges of agricultural grasping

Low cost

Sensors: IMU and IR reflectance
Analysis: CNN with LSTM
Situation: Agricultural Environment

Experimental Setup - Sensors





Experimental Setup – Data Collection

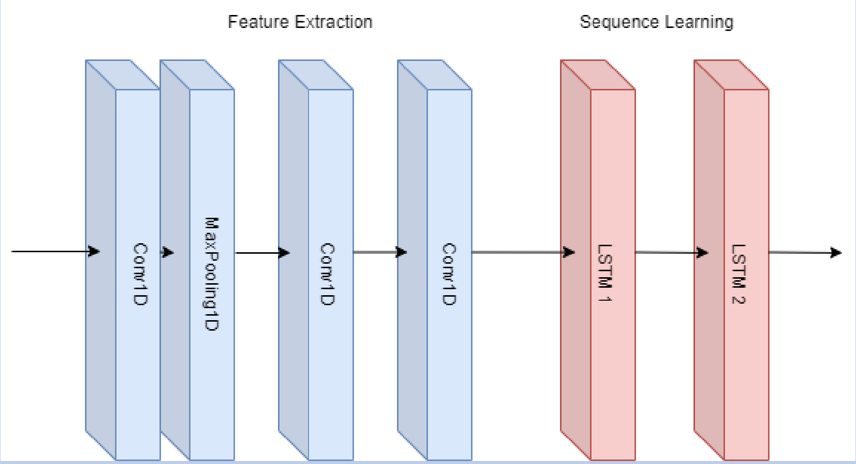
- Using the xArm, the target object is lifted vertically
- A pause is added to increase data variation.
- The target is attached to the workbench with a string causing it to slip and the grasp to fail.
- A force sensor helps label data
- A magnetic sensor provides the target position.

- *** Video Removed***
- Video to ease the explanation of my research method.
- https://youtube.com/shorts/yDJOtUoLcP0

Experimental Setup – Analysis

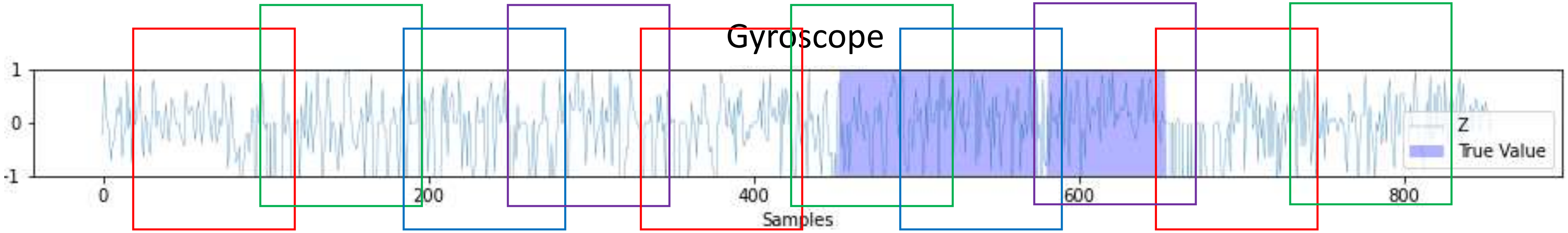
Analysis is done via CNN and LSTM

- CNN extracts data features
- LSTM learns temporal relationship of the data



80% Training,
10% Validation,
10% Testing

More training data is created by selecting small windows of data – from 200 to 1300 sets



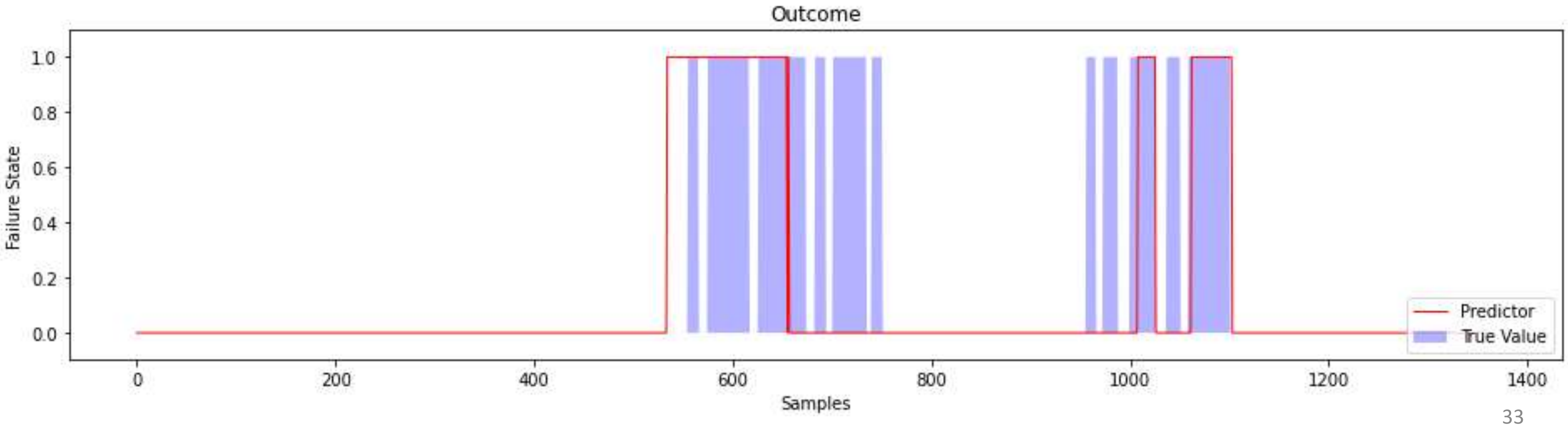
Results and Next Steps

Test for robustness

Train on real cherry tomatoes

Show it works in the field

Respond to the slip detection



Paper's Affect on My Research

This paper is part of the transition of robots from out of the factory and into the living room. I am hope to take the transition one more step – into the field. The paper provides an example of how to do so.

- Performing stabilization
- Generalization
- Random Forests
- Feature functions

Questions?

Additional Background

Human Touch Background

Methods and Sensors for Slip Detection in Robotics: A Survey

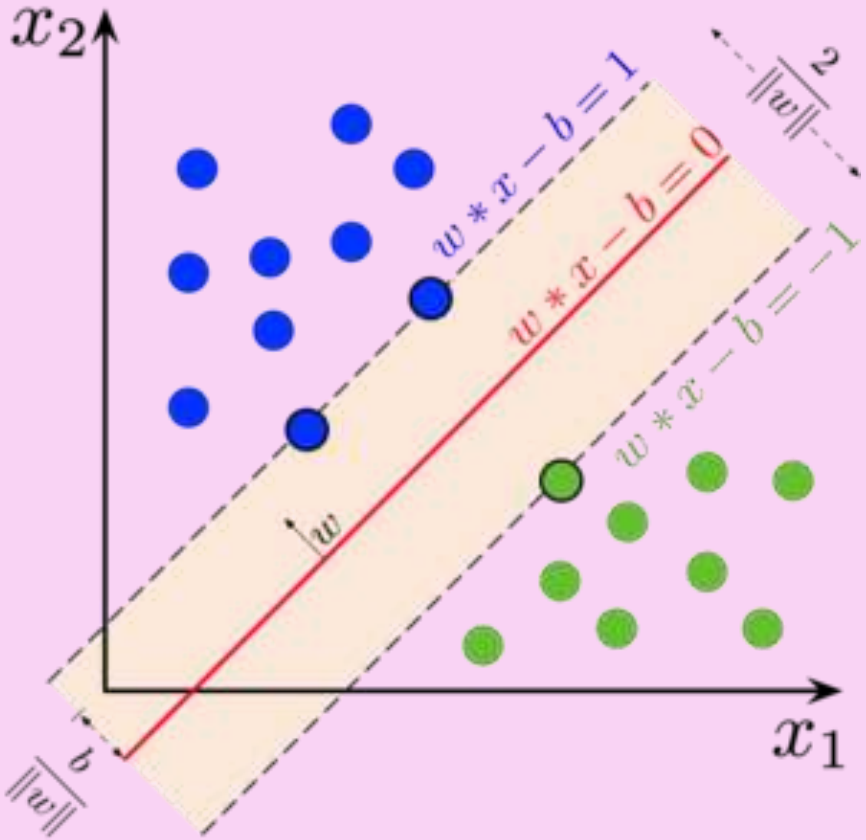
- In particular, FA-I (fast-acting, type one) mechanoreceptors are strongly responsive to localized slips produced by interactions between the dermal papillae and the surface of an object, while deeper FAII mechanoreceptors are particularly receptive to vibrations propagating through the tissues of the hand, such as those produced by a tool interacting with the environment
- FA-I (Fast-Adapting Type One)
- FA-II (Fast-Adapting Type Two)
- SA-I (Slow-Adapting Type One)
- SA-II (Slow-Adapting Type Two)

TABLE 1. Basic properties of human mechanoreceptors.

Name	Receptor type	Field size (mm^2)	Encoded quantity
Meissner Corpuscles	I (fast)	12.6	High frequency vibrations (<50Hz) and acceleration
Pacinian Corpuscles	II (fast)	101	High frequency vibrations (>50 Hz)
Merkel Disks	I (slow)	11	Static load, skin indentation
Ruffini Endings	II (slow)	59	Skin stretch, stretch direction

Support Vector Machine

- Attempt to split data into classes by observing which side of a hyperplane they are on
- Hyperplane is found which maximizes the margin between the support vectors
- Works well when there is a clear separation of data and with lots of features
- Works poorly on large data sets and lacks interpretability



Random Forests

https://towardsdatascience.com/understanding-random-forest-58381e0602d2

- Numerous decision trees are created that have low correlation
- Using the power of consensus, an outcome is predicted
- Works well with large feature sets and is good at rejecting outliers
- Is difficult to tune for best results and has low interpretability

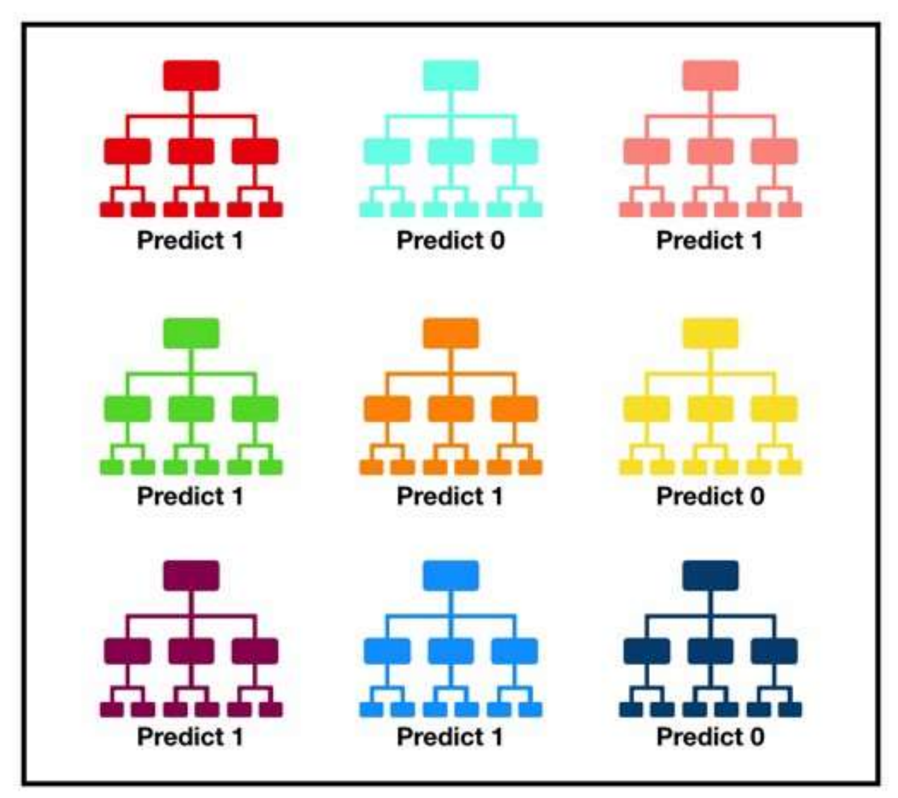


TABLE I

F_{score} FOR VARIOUS COMBINATIONS OF CLASSIFIER AND FEATURES. "PER OBJECT" DENOTES CLASSIFIERS TRAINED INDEPENDENTLY FOR EACH OBJECT. "ALL OBJECTS" REFERS TO TRAINING A SINGLE, GENERAL CLASSIFIER ACROSS ALL OBJECTS. THE BEST PERFORMING METHOD IN EACH COLUMN IS HIGHLIGHTED IN BOLD.

Features	Classifier	Training	F_{score}							
			Mean	Ball	Box	Cup	Marker	Measuring Stick	Tape	Watering Can
$\mathbf{x}_t$	Linear SVM	per object	0.7451	**0.6437**	0.9765	0.7825	0.3258	0.8041	0.9697	0.7137
		all objects	0.7341	0.5065	0.911	0.7114	0.5849	0.9163	0.9749	0.5339
	Random Forest	per object	0.7224	0.2266	0.9775	0.7741	0.6611	**0.9647**	0.9956	0.4571
		all objects	**0.7502**	0.2886	0.9777	0.7437	**0.7049**	0.9126	**0.999**	0.6247
$[\mathbf{x}_t, \Delta\mathbf{x}_t]$	Linear SVM	per object	0.7174	0.6121	**0.9795**	0.7827	0.1495	0.7824	0.9879	**0.7278**
		all objects	0.7336	0.5289	0.908	0.7198	0.5532	0.9328	0.9774	0.5148
	Random Forest	per object	0.7123	0.2462	0.978	0.6922	0.6591	0.9287	0.9963	0.4854
		all objects	0.7097	0.2163	0.9754	0.705	0.6621	0.9192	0.9927	0.4969
$\mathbf{x}_{t-\tau:t}$	Linear SVM	per object	0.7174	0.4132	0.9671	**0.7849**	0.4524	0.7719	0.9069	0.7255
		all objects	0.6571	0.461	0.8141	0.7016	0.3813	0.97	0.8181	0.4535
	Random Forest	per object	0.7212	0.2428	0.9759	0.7297	0.7035	0.9446	0.9941	0.4579
		all objects	0.7151	0.2402	0.9701	0.7067	0.686	0.9227	0.996	0.4841
Chu et al.	Random Forest	per object	0.6956	0.6053	0.9754	0.6862	0.6364	0.8666	0.6778	0.4219
		all objects	0.5374	0.4742	0.9417	0.7026	0.2966	0.7803	0.5181	0.0486
P_{ac}	Spectral Slip	per object	0.2751	0.1237	0.3586	0.2122	0.0796	0.3908	0.4039	0.357
		all objects	0.2565	0.0917	0.3207	0.2071	0.0791	0.3883	0.3714	0.3368

TABLE II

F_{score} FOR VARIOUS CLASSIFIERS IN GENERALIZING TO PREVIOUSLY UNSEEN OBJECTS. THE BEST PERFORMING METHOD IN EACH COLUMN IS HIGHLIGHTED IN BOLD.

Features	Classifier	F_{score}							
		Mean	Ball	Box	Cup	Marker	Measuring Stick	Tape	Watering Can
$\mathbf{x}_t$	Linear SVM	0.5141	0.5432	0.7866	0.4467	0.6384	0.6629	0.0193	0.5019
	Random Forest	0.5936	0.0816	0.8596	0.6966	0.5414	0.6442	0.756	**0.5757**
$[\mathbf{x}_t, \Delta\mathbf{x}_t]$	Linear SVM	0.4788	**0.5639**	0.7718	0.3756	0.5813	0.6453	0.0183	0.3953
	Random Forest	**0.6739**	0.1626	**0.8922**	**0.7076**	**0.7052**	0.7762	**0.9021**	0.5716
$\mathbf{x}_{t-\tau:t}$	Linear SVM	0.4406	0.3997	0.0121	0.6089	0.4554	0.2432	0.843	0.5216
	Random Forest	0.6149	0.0686	0.8235	0.697	0.6975	**0.7906**	0.709	0.518
Chu et al.	Random Forest	0.2926	0.1925	0.8609	0.625	0.0898	0.229	0.0496	0.0017
P_{ac}	Spectral Slip	0.2485	0.0917	0.2957	0.2059	0.0791	0.3758	0.3714	0.3202

TABLE III

F_{score} FOR VARIOUS COMBINATIONS OF CLASSIFIER AND FEATURES WHEN PERFORMING PREDICTION. "PER OBJECT" DENOTES CLASSIFIERS TRAINED INDEPENDENTLY FOR EACH OBJECT. "ALL OBJECTS" REFERS TO TRAINING A SINGLE, GENERAL CLASSIFIER ACROSS ALL OBJECTS. PREDICTION IS DONE FOR 3 DIFFERENT VALUES OF τ_f.

Features	τ_f	Training	F_{score}							
			Mean	Ball	Box	Cup	Marker	Measuring Stick	Tape	Watering Can
$\mathbf{x}_t$	10	per object	**0.717**	0.4255	**0.9715**	0.7324	0.5695	**0.9538**	0.9874	0.3792
		all objects	0.6806	0.2857	0.9233	0.7104	0.4165	0.896	**0.9926**	**0.5395**
	15	per object	0.7047	0.1966	0.9675	0.7334	0.6563	0.9414	0.9862	0.4513
		all objects	0.6427	0.2369	0.9532	0.7188	0.3081	0.8949	0.9255	0.4617
	20	per object	0.6795	0.0938	0.9661	0.7274	0.6767	0.9241	0.9471	0.4211
		all objects	0.6989	**0.4626**	0.9359	0.6948	0.4034	0.8991	0.9732	0.5232
$[\mathbf{x}_t, \Delta\mathbf{x}_t]$	10	per object	0.6797	0.0937	0.9685	0.7361	0.602	0.9163	0.9885	0.4528
		all objects	0.6743	0.0865	0.9665	0.7149	0.6041	0.914	0.9912	0.4429
	15	per object	0.6918	0.1294	0.9615	0.7385	**0.7228**	0.866	0.9823	0.4422
		all objects	0.6727	0.32	0.9561	0.7119	0.4001	0.9101	0.9776	0.433
	20	per object	0.6918	0.0972	0.964	**0.7439**	0.7145	0.9235	0.9721	0.4273
		all objects	0.6697	0.3275	0.9592	0.7161	0.4497	0.8983	0.9741	0.3626

TABLE IV

F_{score} FOR VARIOUS CLASSIFIERS IN GENERALIZING TO PREVIOUSLY UNSEEN OBJECTS WHEN PERFORMING PREDICTION. THE BEST PERFORMING METHOD IN EACH COLUMN IS HIGHLIGHTED IN BOLD.

Features	τ_f	F_{score}							
		Mean	Ball	Box	Cup	Marker	Measuring Stick	Tape	Watering Can
$\mathbf{x}_t$	10	0.5266	0.1741	0.4054	**0.7017**	0.4032	0.7101	0.6281	0.6638
	15	0.564	0.2315	0.5874	0.6507	0.2373	0.7819	0.7739	**0.685**
	20	0.5962	0.1643	0.7936	0.669	0.4432	0.7558	0.759	0.5885
$[\mathbf{x}_t, \Delta\mathbf{x}_t]$	10	**0.6406**	0.1943	**0.8154**	0.6965	**0.5778**	0.7678	**0.9502**	0.4819
	15	0.5562	**0.2326**	0.4383	0.6909	0.4278	**0.8036**	0.8765	0.4239
	20	0.5337	0.1667	0.5861	0.6906	0.3724	0.7763	0.879	0.2649

TABLE V

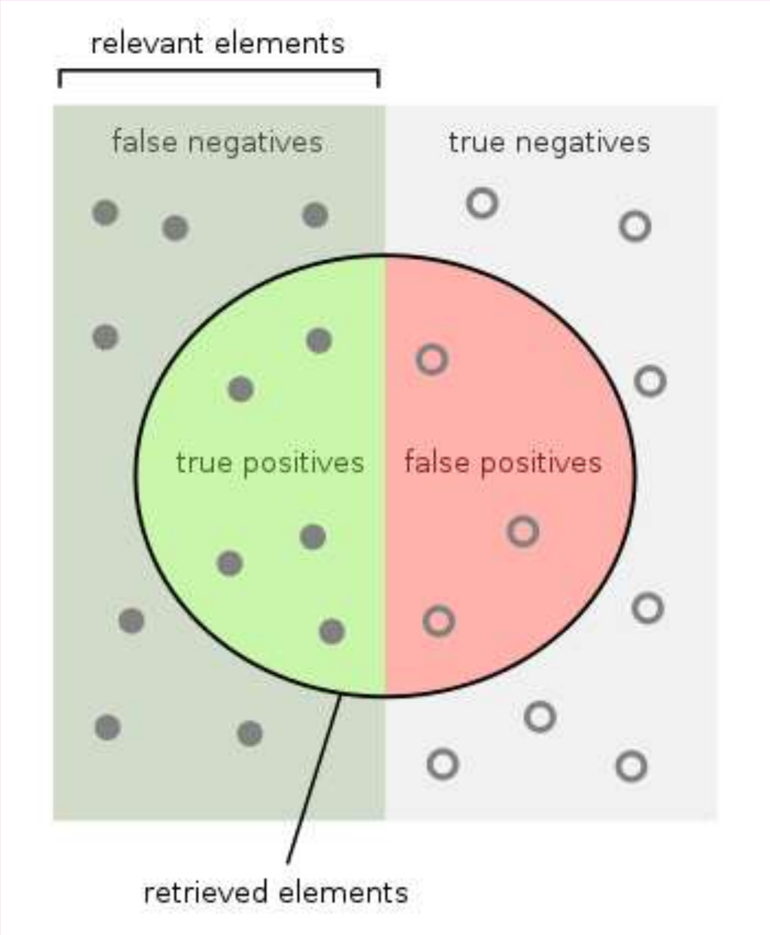
PERCENTAGE OF SUCCESSFUL GRIP STABILIZATION TRIALS USING OUR GRIP STABILIZATION CONTROLLER. ALL CONTROLLERS USED A RANDOM FOREST SLIP CLASSIFIER TRAINED WITHOUT DATA FOR THE TEST OBJECT. BOLD VALUES INDICATE THE BEST PERFORMANCE FOR A GIVEN OBJECT.

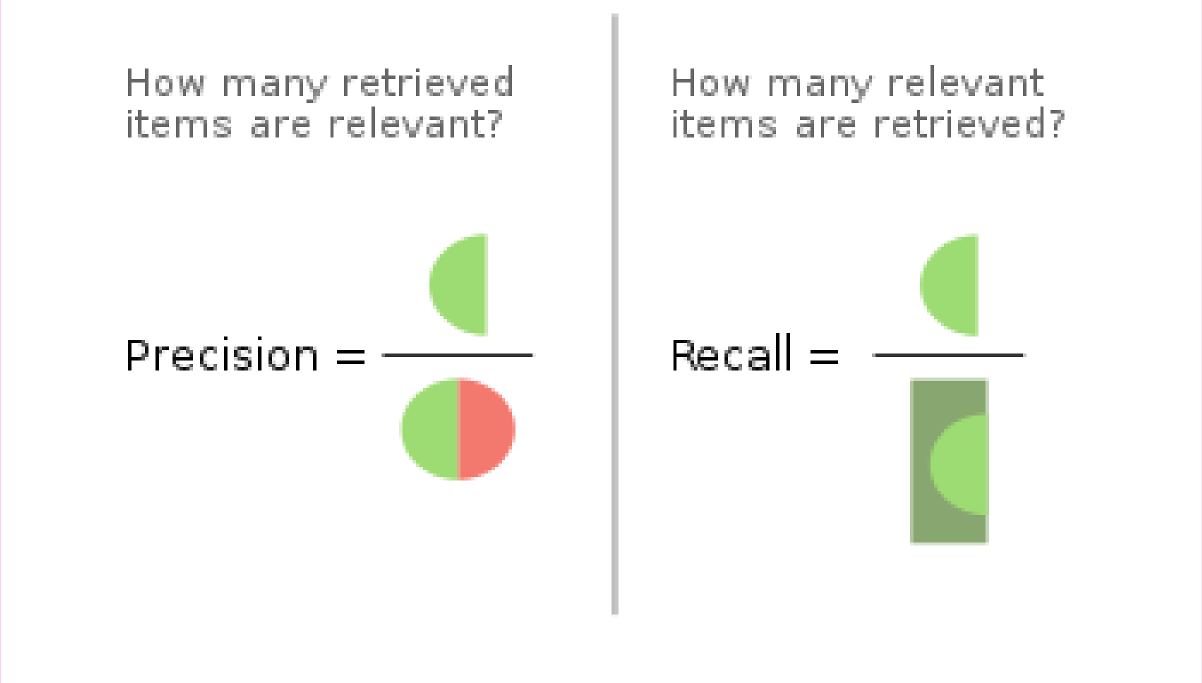
Test Object	$\mathbf{x}_t$				$[\mathbf{x}_t, \Delta\mathbf{x}_t]$			
	$\tau_f = 0$	$\tau_f = 10$	$\tau_f = 15$	$\tau_f = 20$	$\tau_f = 0$	$\tau_f = 10$	$\tau_f = 15$	$\tau_f = 20$
Ball	0%	0%	0%	**100%**	90%	0%	90%	80%
Box	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	90%	**100%**
Cup	90%	60%	40%	70%	**100%**	10%	60%	60%
Marker	80%	40%	80%	10%	30%	10%	0%	**100%**
Measuring Stick	20%	**90%**	60%	10%	20%	10%	0%	10%
Tape	10%	**100%**	80%	**100%**	30%	80%	**100%**	90%
Watering Can	10%	60%	**100%**	50%	30%	60%	60%	80%
Overall	44.28%	64.28%	65.71%	62.85%	57.14%	38.57%	57.14%	**74.28%**

Precision and Recall Example

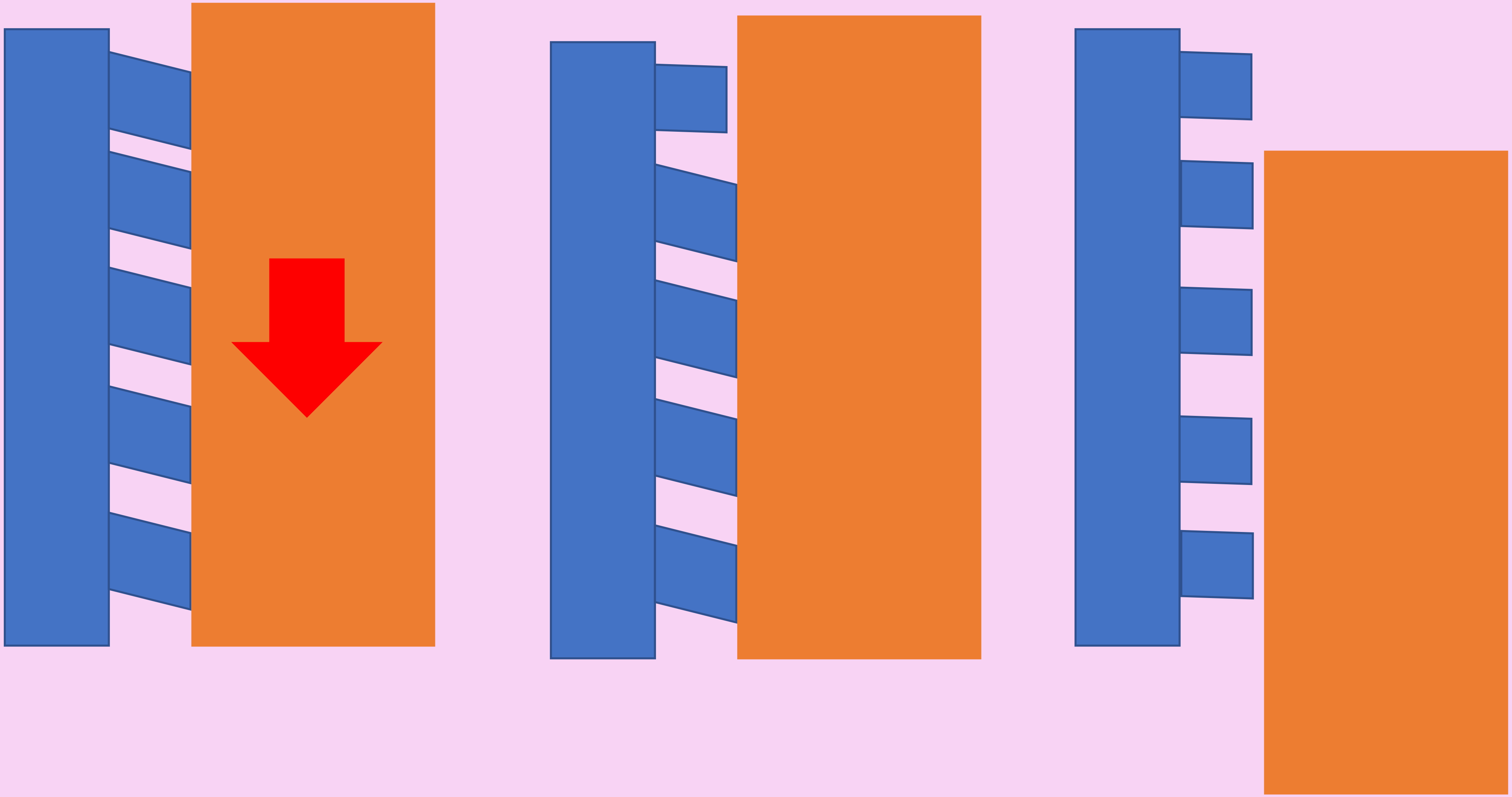
- Situation: A computer vision algorithm wants to identify all the dogs in a picture of cats and dogs
- Precision – Good precision is labelling only dogs as dogs (even if some dogs are labelled cats) – no cats labelled dog.
- Recall – Good recall is finding all of the dogs (even if a few cats are labelled dogs)

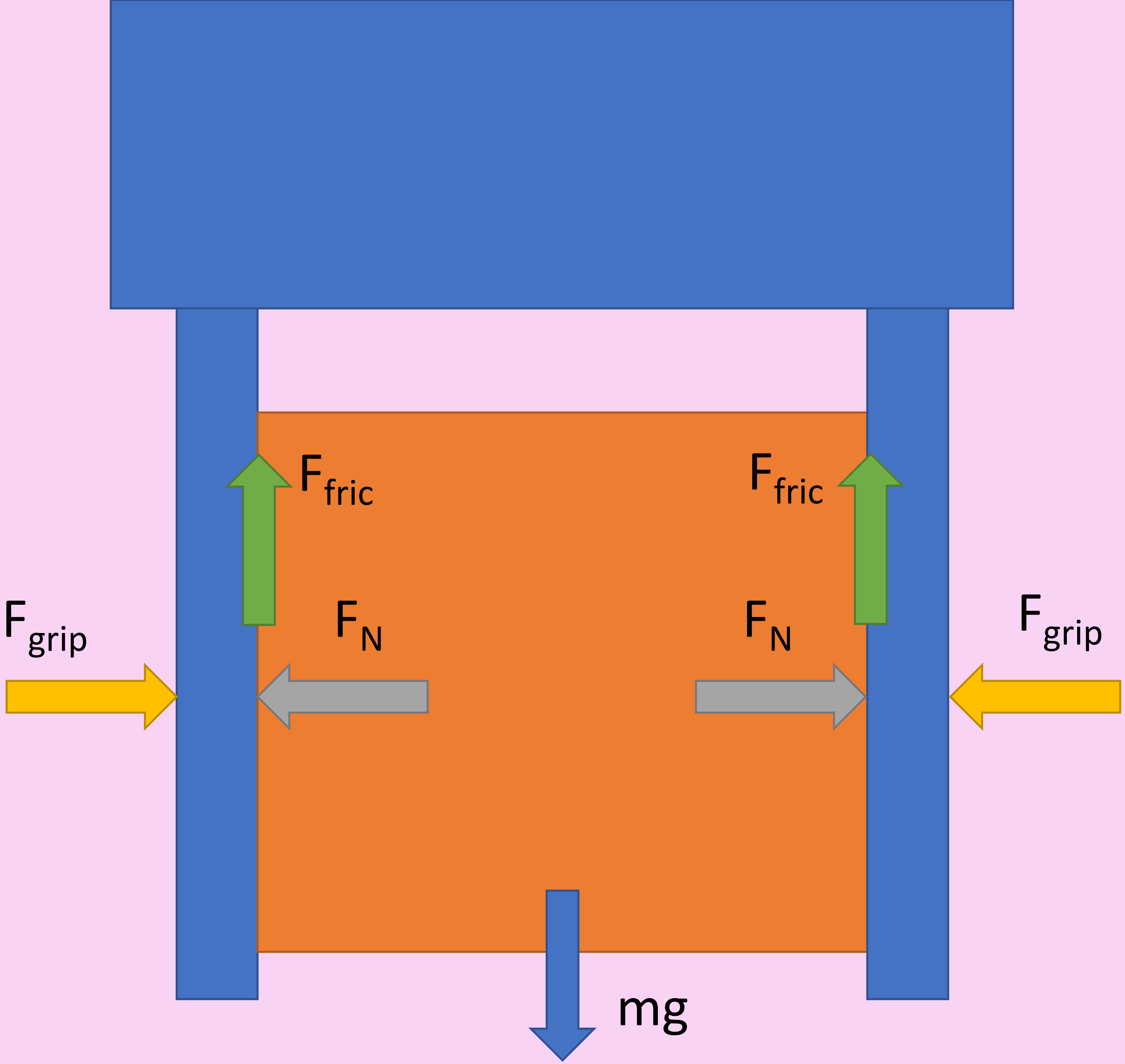
Precision and Recall



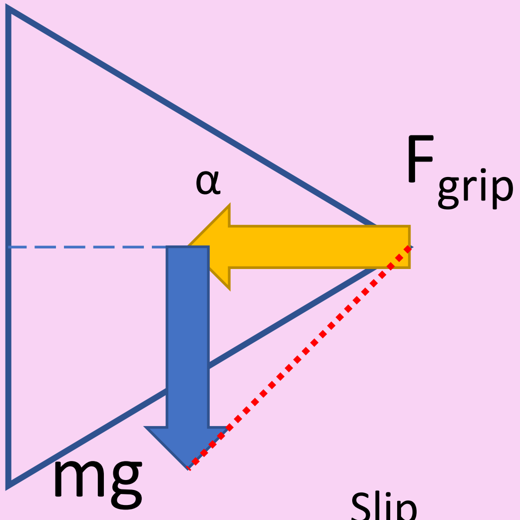


Incipient Slip

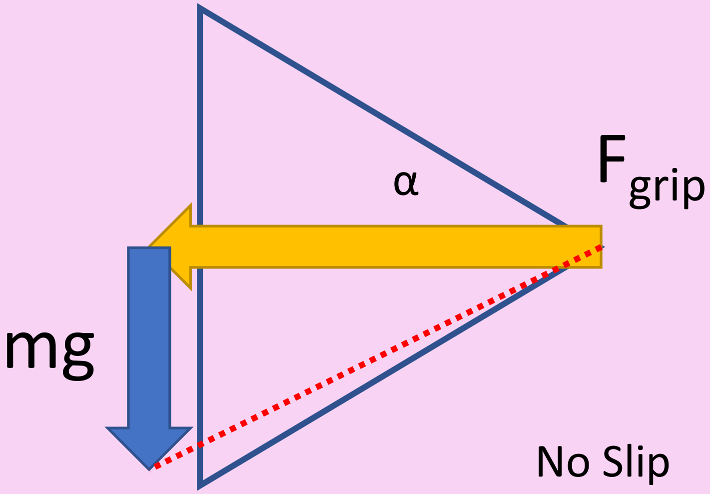




F fric
F fric
F grip
F N
F N
F grip
mg



α
F grip
mg
Slip



α
F grip
mg
No Slip

Fixing controller

- Simple – as force is known, set an upper bound
- May need some external signal to help with this
  - Humans have eyes that can tell us when additional force is not working (think of an oily, heavy object
  - Could a secondary analysis of the same data help? Like a different method of detection to verify it. At least if you could have a high confidence that slip is not happening (but it that the same as having a high confidence that slip is happening or does the confusion matrix play a role here…)
- Create a loosening effect – after so long without slip, slowly loosen the force until slip is predicted again – doesn't fix unboundedness

SVM Equation Notes

A classifier

$$g(\mathbf{x}) = \operatorname{sgn}\left(\tilde{\mathbf{w}}.\mathbf{x} + w_0\right)$$
$$= \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i y_i (\mathbf{x}_i.\mathbf{x}) + w_0\right).$$

Regression

$$f(\mathbf{x}) = \sum_{i=1}^{n} \beta_i k(\mathbf{x}, \mathbf{x}_i) + w_0,$$

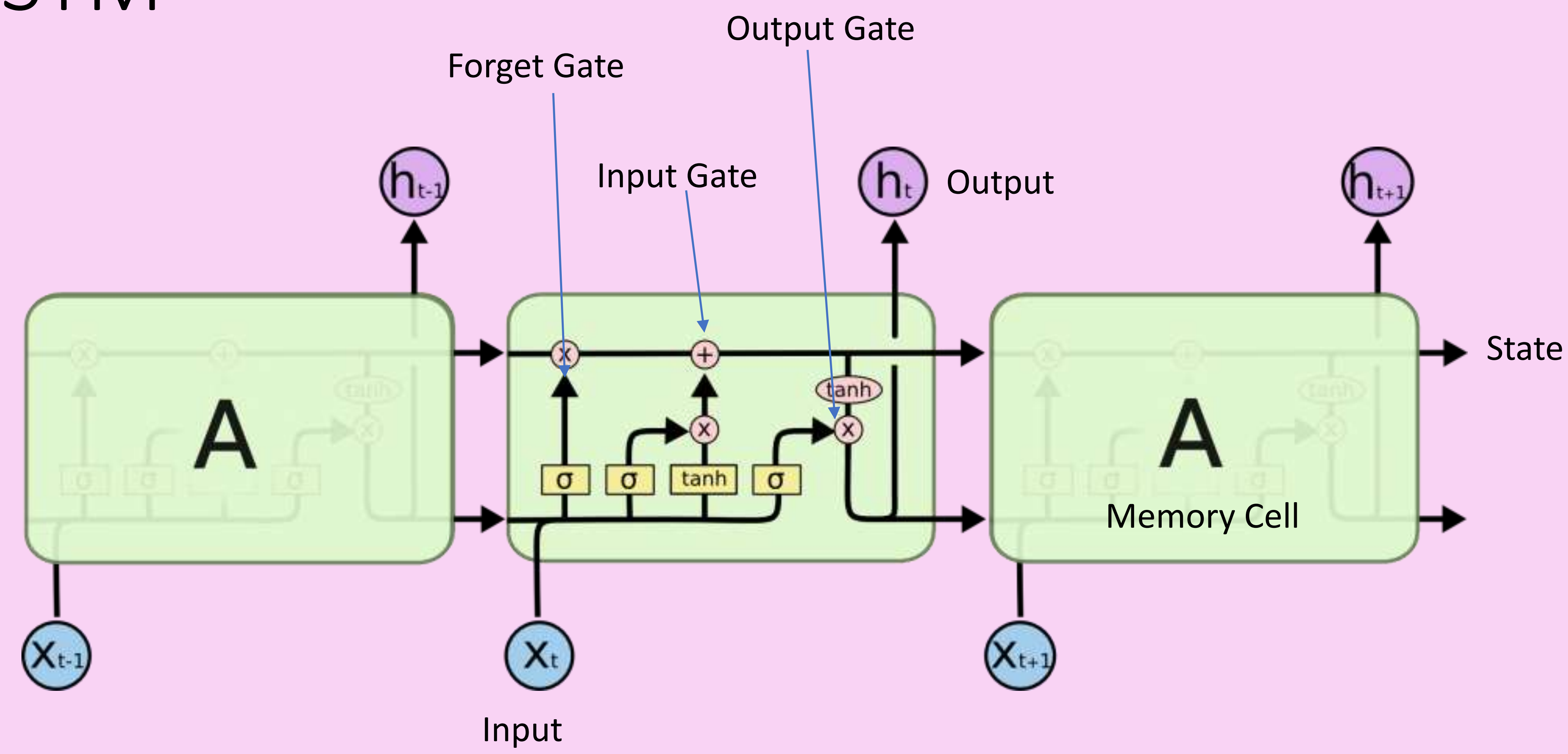
Paper
(also Regression, but should be classifier)

$$f(\mathbf{z}) = \sum_{i=1}^{k} {}^{i}\alpha(\mathbf{z} \cdot {}^{i}\mathbf{z}) + b$$

Authors

- Filipe Veiga (Student)
  - Focus is on Robot learning – especially in manipulation and tactile sensing
  - This and follow up are only slip based papers
- Herke Van Hoof (Student?)
  - Focus is on Robot learning – especially RL
  - Number of manipulation papers
- Jan Peters
  - Focus is on Robot learning – especially RL
- Tucker Hermans
  - Focus is on manipulation, motion planning and learning
  - CS/AI focus

LSTM



https://colah.github.io/posts/2015-08-Understanding-LSTMs/

A mechanical hand with automatic proportional control of prehension (1967)

- A technical note
- Developed for prosthesis
- Uses a piezo crystal (from a record player) to detect vibration due to slip
- Uses same basic control scheme as today's paper
- Converts vibration to discrete pulses to drive the motor to close the fingers more.

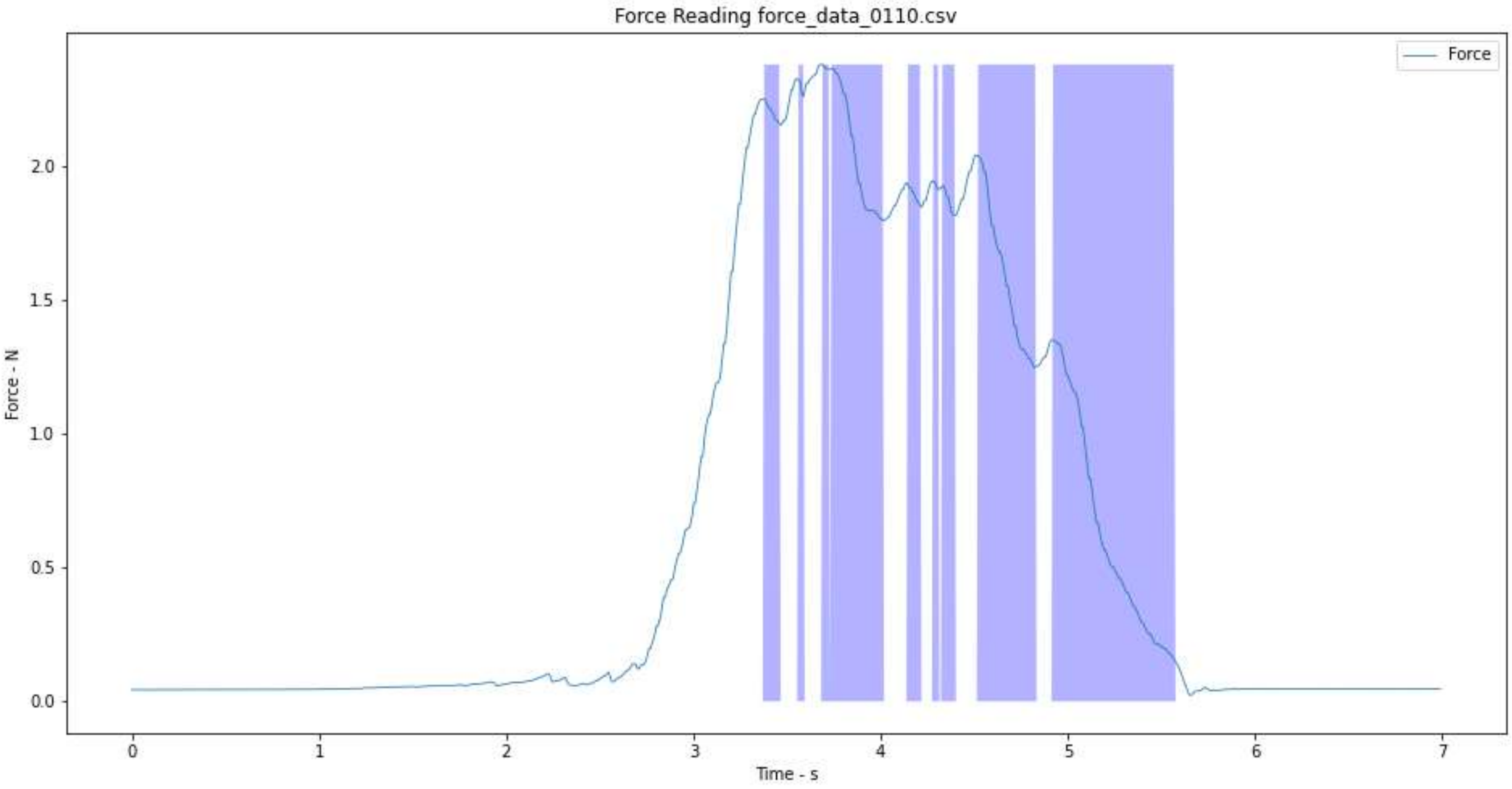
Estimating Friction Using Incipient Slip Sensing During a Manipulation Task

- Uses an accelerometer to measure small vibrations during slip
- A second accelerometer is used to reject vibrations not related to the slip (Such as tapping the testing rig)

Detection of incipient object slippage by skin-like sensing and neural network processing

- First use of a NN for slip detection
- Uses a multilayer perceptron
- Authors note the lack of quality tactile sensors
  - Used simulation instead
  - Do a real test, but note the poor results due to the small, 1D sensor.

Rigid Mount



Force Reading force_data_0110.csv
Force
2.0
1.5
1.0
0.5
0.0
Force - N
0
1
2
3
4
5
6
7
Time - s

Common Sensors

Can I make this slide more interesting with some images?

- Force
- Vibration
  - Piezoelectric and acoustic signals
  - Allows use of FFT, STFT, DWT and other audio signal techniques such as filters
- Optical
- Velocity/Acceleration – using Laser Doppler Velocimeter, accelerometer (close connection with vibrations)
- Thermal
- Magnetic
- Tactile arrays

Common Analysis Methods

- Estimation of Physical properties – forces, friction, slip margin
- Signal Processing - FFT/STFT/DWT/Filters
- ML
  - Neural Network
  - SVM
  - Random Forrests
  - Gaussian Processes
  - LSTMs
- Computer Vision techniques
  - Using actual images
  - Treating data like images

Can I make this slide more interesting with some images?

Human-Inspired Robotic Grasp Control With Tactile Sensing (2011)

- Uses bio-inspired tactile sensors mounted on a PR2 robot
- Source of control scheme
- Looks at the full grasping timeline

Using robotic exploratory procedures to learn the meaning of haptic adjectives (2013)

- BioTac sensors are used to apply adjective labels to objects
  - Adjectives such as: rough, solid, thin, cool,…
- Feature functions are used to extract features from raw data and aid in learning
  - Functions are designed to focus on certain aspects, such as:
    - Compliance
    - Texture
    - Thermal conductivity
- Referenced as Chu et al. in the paper

Experimental Comparison of Slip Detection Strategies by Tactile Sensing with the BioTac on the DLR Hand Arm System (2014)

- Objects are lifted by a two-finger gripper with BioTac sensors fitted. The object can be caused to slip by a wire attached to a motor.
- Explores 3 slip detection strategies
  - Model based via friction cone
  - Signal processing using a bandpass filter
  - Learning based – Using a Random Forest
- Also uses the same basic control scheme as the reviewed paper

Multimodal Tactile Sensor (2014)

- Detailed walkthrough of the BioTac sensor by the creators.
- Gives some basic validations of its ability to:
  - Measure force
  - Sense vibration
  - Differentiate texture
  - Detect slip (with a bandpass filter)
  - Sense temperature and heat flow