

NSF CAREER Awardees



Moderated by: Dr. Frank A. Gomez Executive Director, STEM-NET Office of the Chancellor



https://www2.calstate.edu/impact-of-the-csu/research/stem-net

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Speakers

George Youssef, San Diego State

Light-matter Interactions for Mechanics of Nontraditional Materials

Ava Hedayatipour, Cal State Long Beach

CISE-MSI: Towards Efficient, Reliable, and Secure Chaotic Communications in Wearable Devices

Yu Yang, Cal State Long Beach

Global Optimization of Chance-Constrained Programming for Reliable Process Design

Wencen Wu, San Jose State Multi-Robot Exploration of Spatial-Varying Fields

Long Wang, Cal Poly San Luis Obispo Characterization and Detection of Corrosion Damage



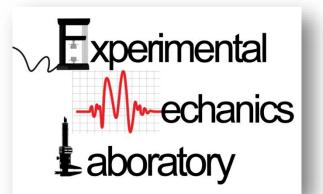


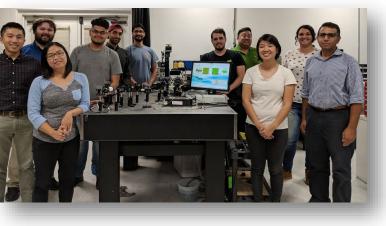
Light-matter Interactions for Mechanics of Nontraditional Materials

George Youssef, Ph.D., P.E.

Experimental Mechanics Laboratory, *Principal Investigator* Mechanical Engineering, *Professor* San Diego State University, CA, U.S.A.

CSU Exemplars in Engineering Webcast – October 4th, 2023







Mechanics of Nontraditional Mat

Advancing Mechanics

and

Broadening Participation in Engineering

Underrepresented minorities and women







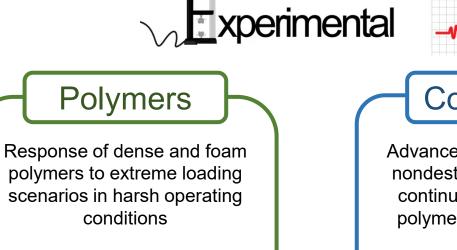












Physical Mechanical Thermal Dynamic Composites

M_m-echanics

Advanced manufacturing and nondestructive evaluation of continuous fiber reinforced polymer matrix composites

Robotic 3D printing Terahertz NDE Data-driven detection Laboratory

Multifunctional

Strategically leverage solid and structural mechanics to inspire multi-functionality

Load Management Heat Management Fluid Management Electrical Management

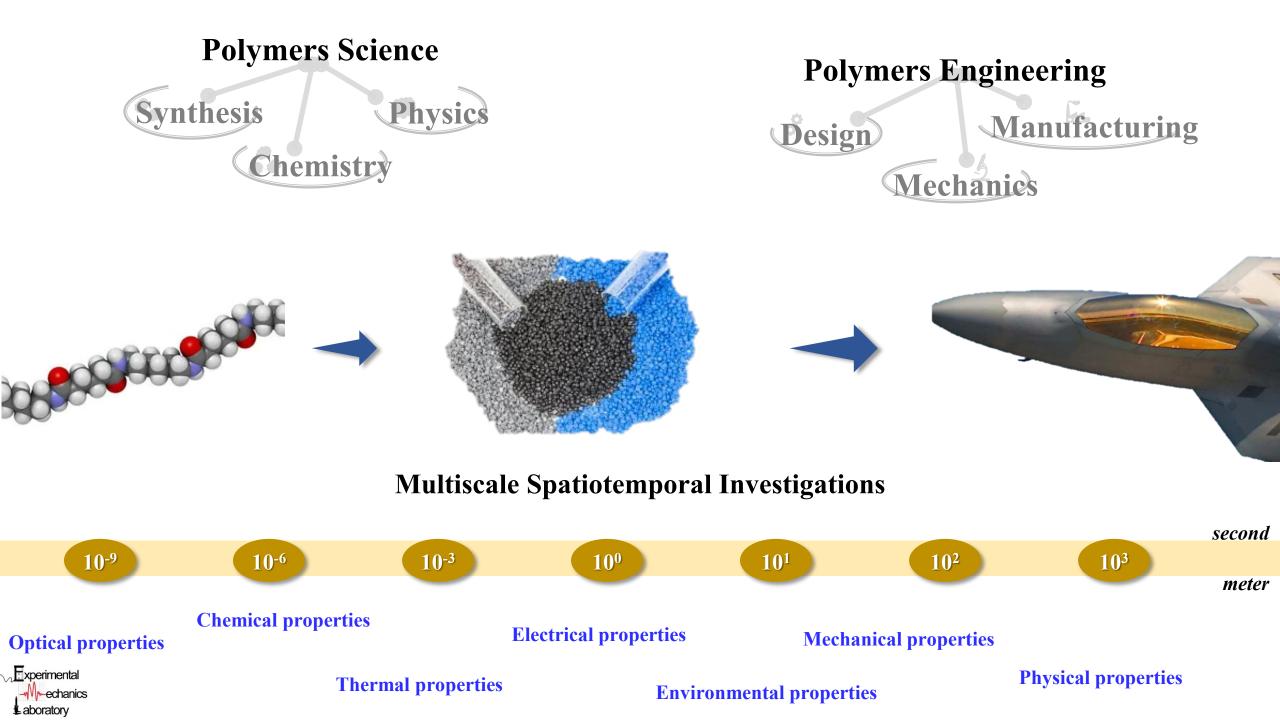


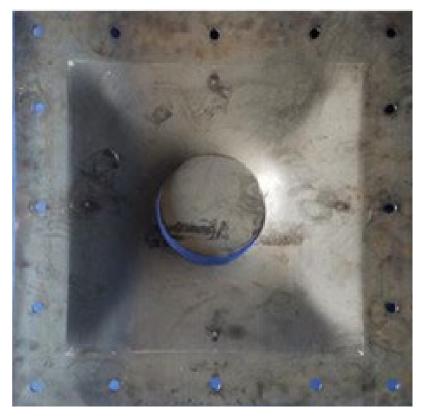




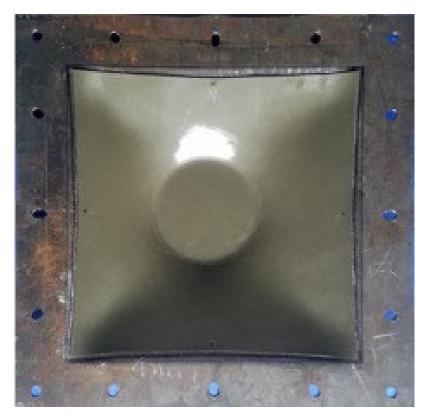


EML focuses on lightweight and multifunctional materials



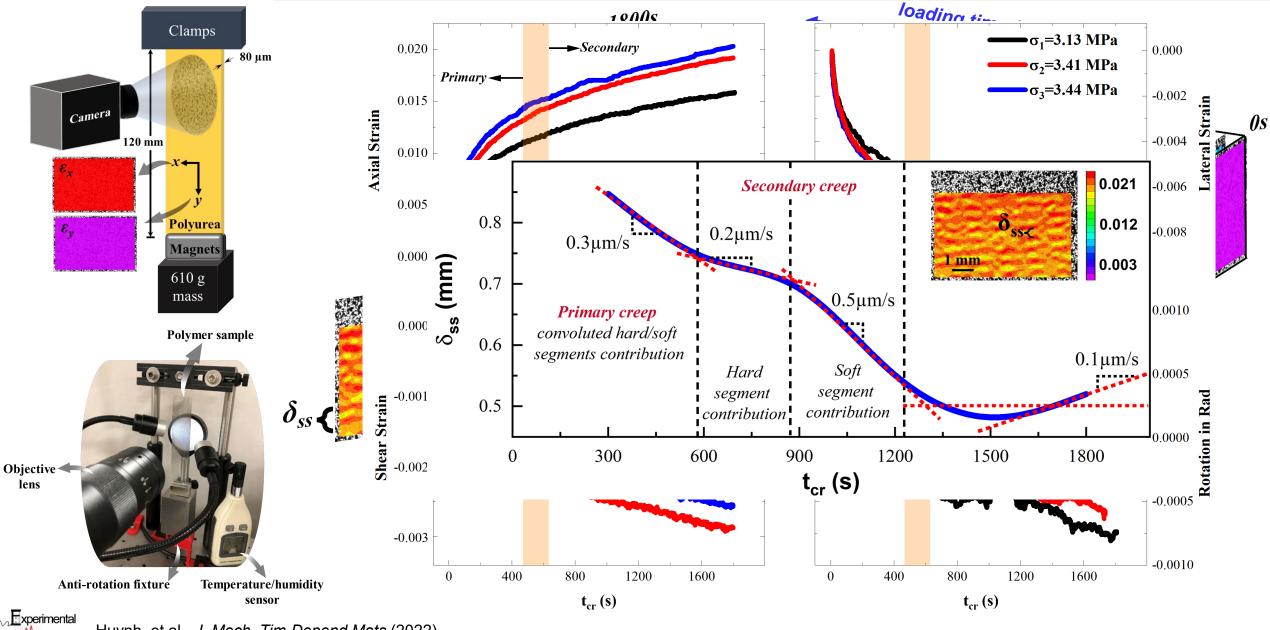


Steel armor plate without protective coating



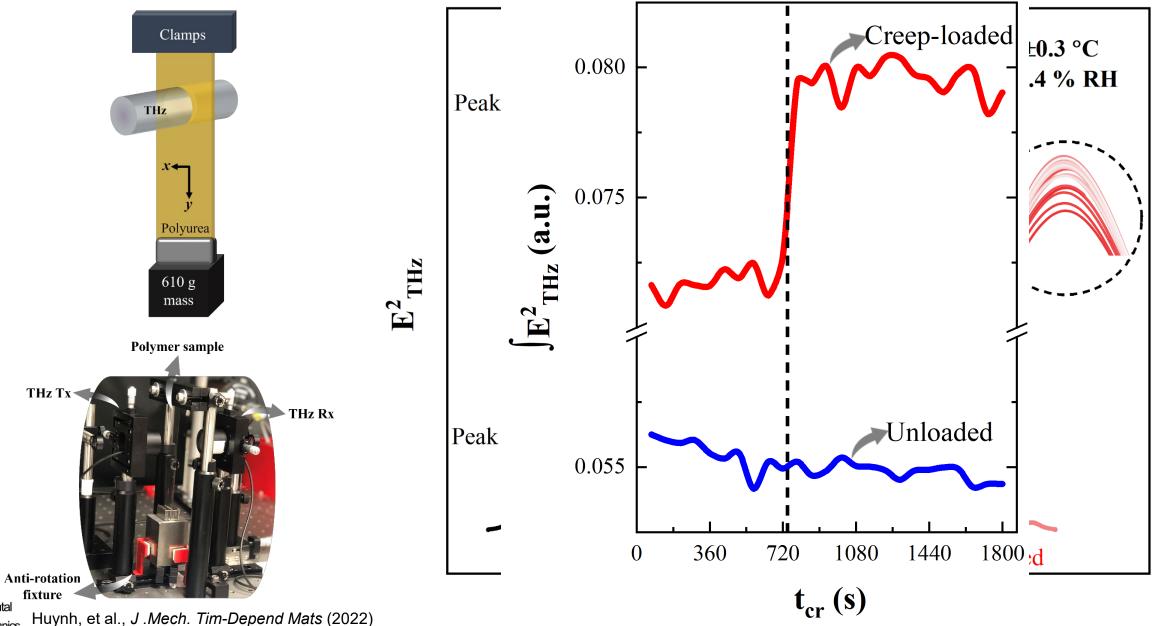
Steel armor plate with polyurea protective coating

Full-field Creep Results



Huynh, et al., *J .Mech. Tim-Depend Mats* (2022) Huynh et al., *Macromolecular Rapid Communications* (2023)

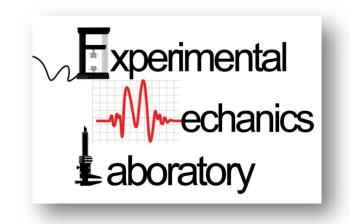
THz-TDS Results – Time Domain



-echanics Huynh et al., Macromolecular Rapid Communications (2023) Laboratory

fixture

Experimental

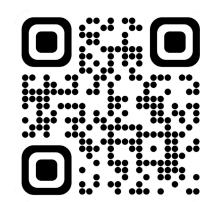




Advancing Mechanics

and

Broadening Participation in Engineering



gyoussef@sdsu.edu



space ARMORCAST















Ava Hedayatipour– Department of Electrical Engineering (EE), California State University Long Beach

Collaborators: Dr. Amin Rezaei, Dr. Hossein Sayadi, Dr. Mehrdad Aliasgari, Department of Computer Engineering & Computer Science (CECS) California State University Long Beach

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Autonomous Cars¹¹

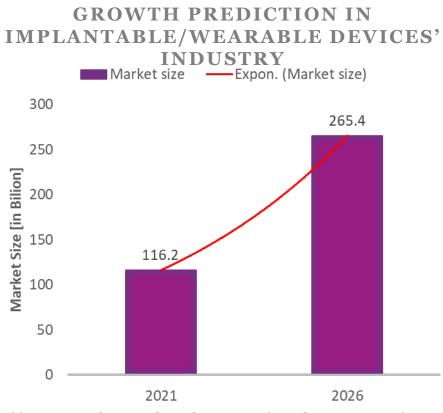






Project Overview

Glance to the Future



https://www.marketsandmarkets.com/Market-Reports/wearableelectronicsmarket-983.html, Apr 2021.





Project Overview Encryption Algo

- Symmetric Encryption:
 - * The shared private key between sender and receiver.
 - * Fast, less computing, but not considered reliable communication. Example:

Advanced Encryption Standard (AES)

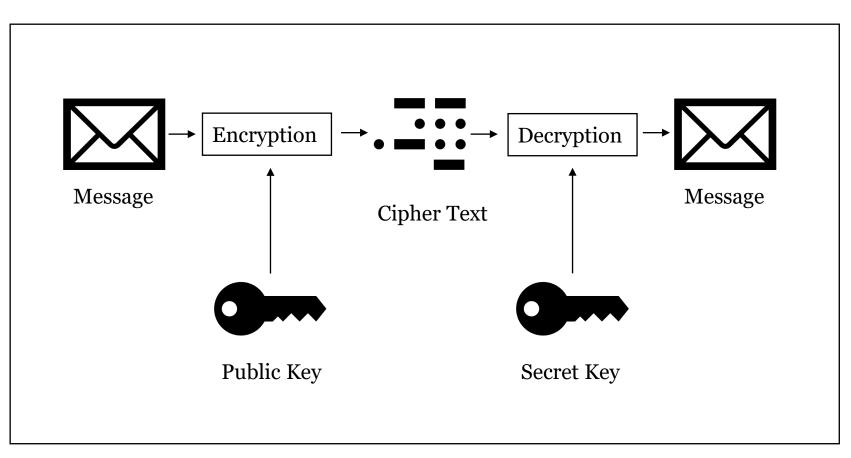
Asymmetric Encryption:

- * The sender provides the public information and the receiver decrypts that with the private information
- * Higher computational requirements and factorization complexity
- * Example: Rivest Shamir Adelman (RSA) and the Diffie-Hellman (DH)

| | Algorithm | Purpose |
|-----|--|--|
| and | Advanced encryption standard (AES) | Confidentiality |
| ed | Rivest Shamir Adelman (RSA)/ Elliptic Curve Cryptography (ECC) | Digital signatures key transport |
| | Diffie-Hellman (DH) | Key agreement |
| | SHA-1/SHA-256 | Integrality |



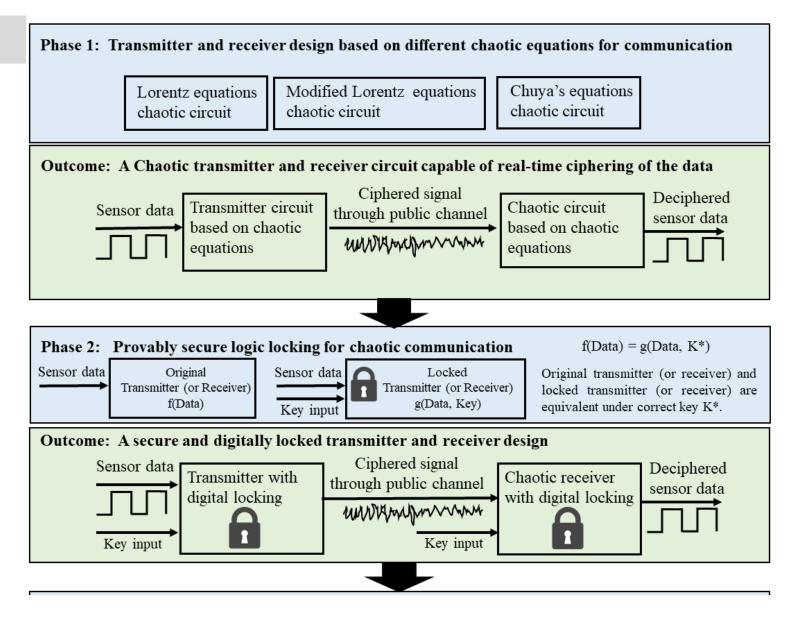
Project Overview



Asymmetric cryptography

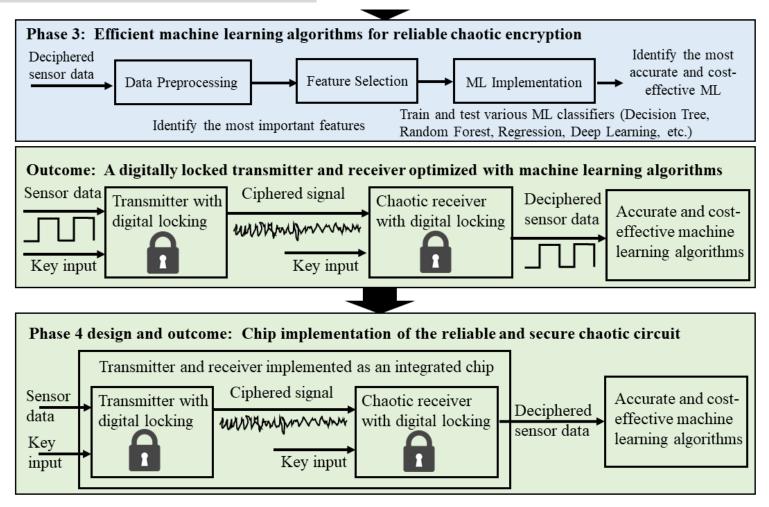


Project Overview





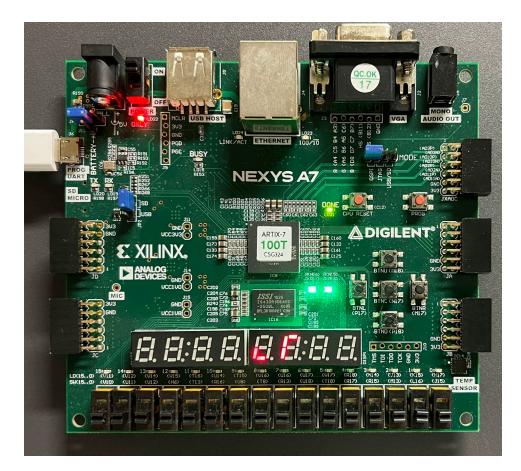
Project Overview



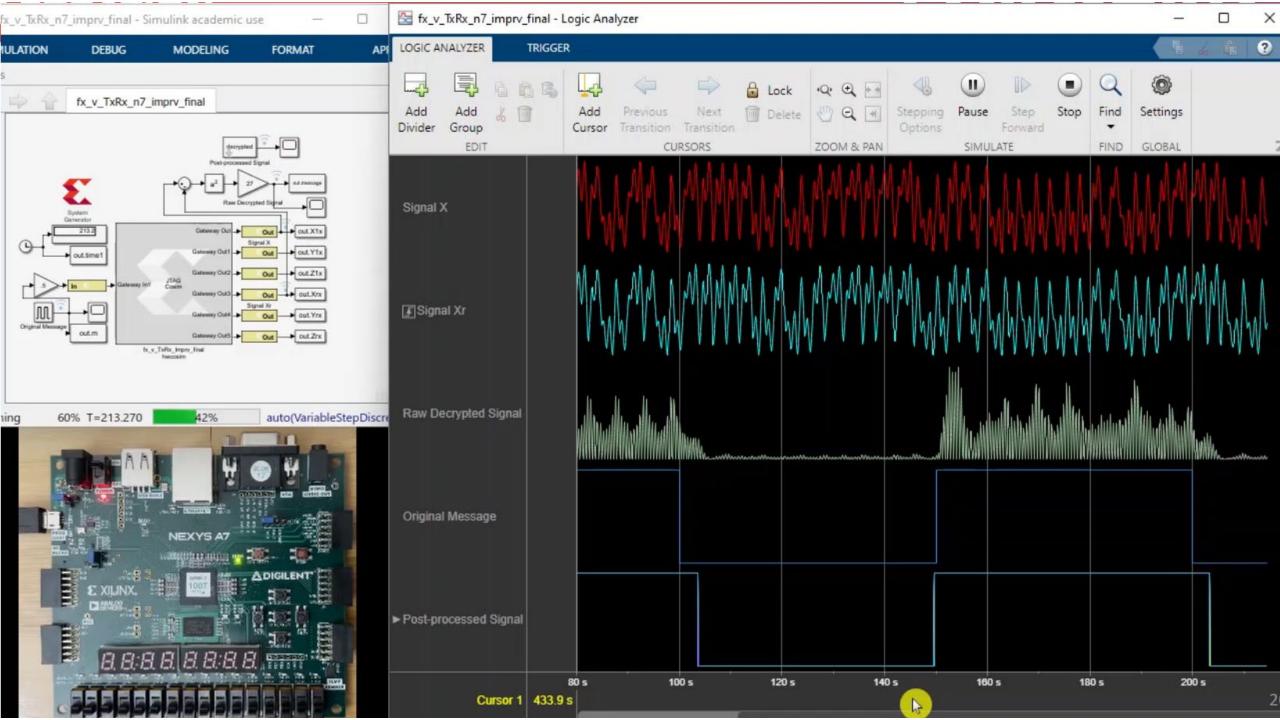


Results

- Demonstration of encryption architecture on Xilinx's Digilent Artix7Nexys7 FPGA board.
- The JTAG port has been used to deliver the computation to the board and bring back the results.



Xilinx FPGA Board₇₉NEXYS A7





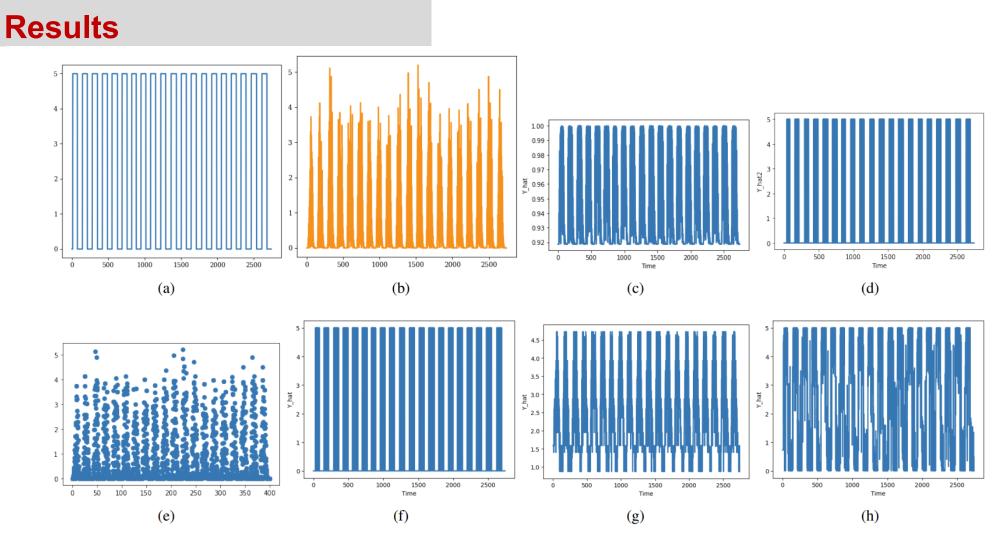


FIGURE 5. Different machine learning algorithms used in signal synchronization (a) Original message (b) Decoded message (MSR: 13.00) (c) LSTM synchronization (d) K-means synchronization (MSR: 6.96) (e) DBSCAN synchronization (MSR: 12.56) (f) SVM synchronization (g) AdaBoost synchronization (MSR: 3.52) (h) RF synchronization (MSR: 4.00)



Lessons Learned

- If you are the main PI be ready to PUSH.
- Things **rarely** move forward without follow-ups.
- Have alternative planning in line.
- The program director is a friend, not a foe.



Next Steps/Long-Term Plans

- To expand the scope of the design and get experimental data for real-world bio-medical signals, i.e, ECG.
- To achieve the initial goal with which this research began, implement the efficient and low-power chaotic encryption circuit on-chip
- To make the design robust and eliminate the flaws, carry out the testing/validation against attacks.

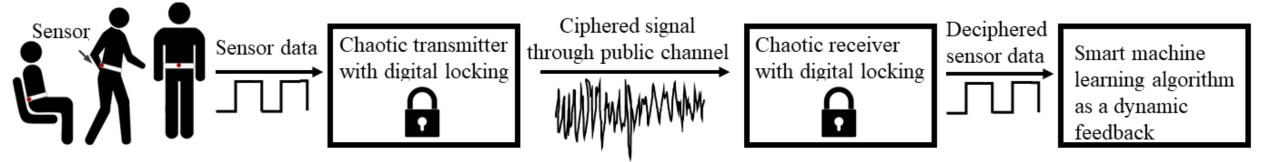
Acknowledgment

This material is based upon work supported by the National Science Foundation under Grant No. 2131156. The work presented is the work of my brilliant students.



Summary

CISE-MSI: Towards Efficient, Reliable, and Secure Chaotic Communications In Wearable Devices





Questions?

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Global Optimization of Chance-Constrained Programming for Reliable Process Design

Dr. Yu Yang California State University Long Beach

Dr. Yu Yang, Associate Professor

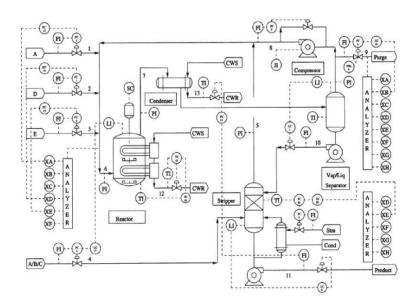
CSULB, Department of Chemical Engineering

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Motivation

 Incomplete knowledge of mathematical models used for the optimization-based design of chemical processes can lead to degraded quality of fuels, vaccines, manufactured foods, and other chemical products, giving rise to economic, safety, health, and environmental issues.

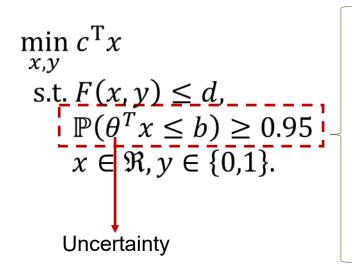






Project Overview

Chance-constrained Programming (CCP)



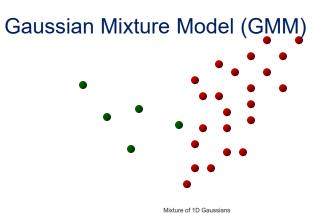
Random Algorithm: Scenario Approximation, Scenario Tree

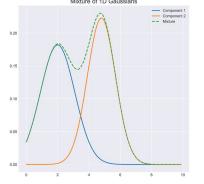
Analytical Approach: Distribution-based (Only applicable for Gaussian distribution)



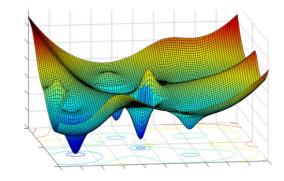
Project Overview

Data-Driven Modeling and Global Optimization





Global Optimization

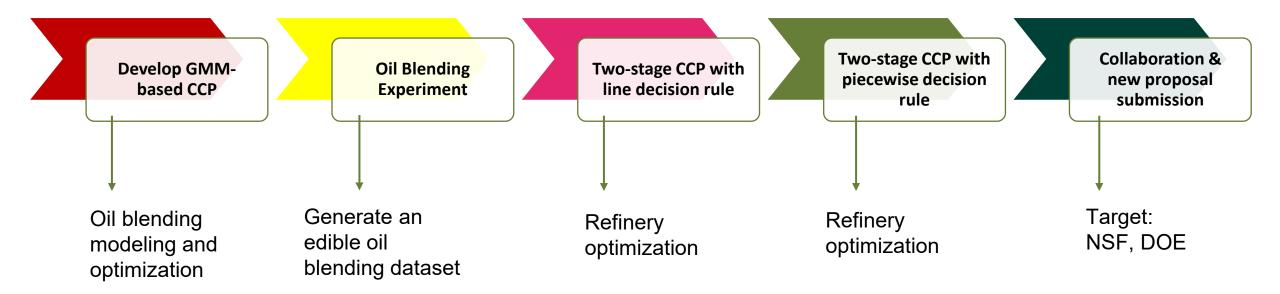


- Convex relaxation>>Second-order cone relaxation
- Branch-and-Bound
- Bound tightening
- Reformulation linearization technology
- Piecewise linear decision-rule



Project Overview

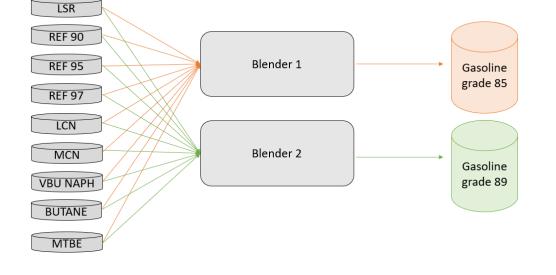
• Theoretical and Experimental Research





Activities (Single Stage GMM-CCP)

• Oil Blending (Linear Programming)



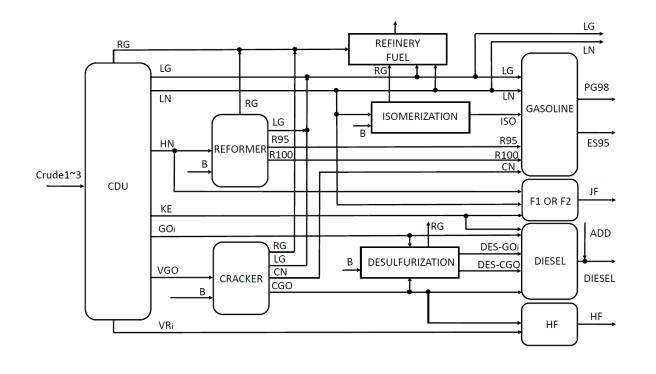
Objective: Determine the blending receipt such that the profit is maximized, and quality specifications are met with high chance (>95%)

| | GMM-CCP | Scenario Average (SA) |
|-------------------|--------------------------------|-----------------------------------|
| Profit: | \$378.49 | \$354.60 |
| Solution time: | 6,668 s | 101 s |
| Conclusion: | Slow but guaranteed optimality | Fast but needs significant tuning |



Activities (Two-Stage GMM-CCP)

Refinery Optimization (Mixed-integer linear programming)



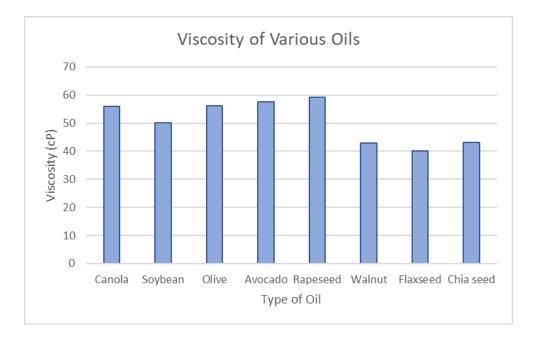
Objective: Determine the crude oil procurement (State-I) and refinery operations (Stage-II) to maximize the profit and meet the quality specification with high chance.

| | GMM-CCP + Decision-Rule | Scenario Tree |
|-------------------|--------------------------------------|----------------------|
| Profit: | \$102,467,704 | \$101,282,597 |
| Solution time: | 4709 s | 7224 s |
| Risk: | 2.4%<5% | 2%<5% |
| Conclusion: | Faster, Scalable, More profitable | Slower, Non-scalable |



Activities

• Student Project: Optimization of Blended Vegetable Oil with Viscosity Constraint









Lessons Learned

• Pre-award: Preliminary data and publication are important to the NSF grant application.

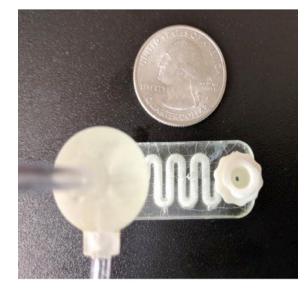
• Yang, Y. (2019). Improved Benders decomposition and feasibility validation for two-stage chance-constrained programs in process optimization. *Industrial & Engineering Chemistry Research*, 58, 4853-4865.

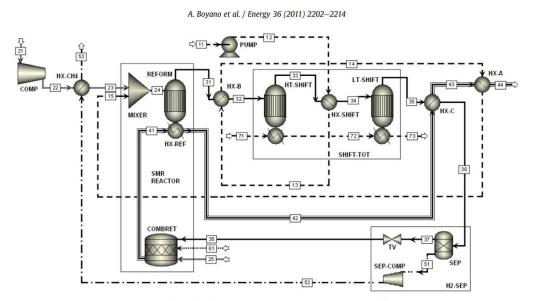
- Yang, Y., dela Rosa, L., Chow, T. (2020). Non-convex chance-constrained optimization for blending recipe design under uncertainties. *Computers & Chemical Engineering*, 139, 106868.
- Yang, Y. and Sutanto, C. (2019). Chance-constrained optimization for nonconvex programs using scenario-based methods. ISA Transactions, 90, 157-168.
- Yang, Y., Vayanos, P., Barton, P. (2017). <u>Chance-constrained optimization for refinery blend planning under uncertainty</u>. *Industrial & Engineering Chemistry Research*, 56, 12139-12150.
- Yang, Y. (2019). Improved Benders decomposition and feasibility validation for two-stage chance-constrained programs in process optimization. Industrial & Engineering Chemistry Research, 58, 4853-4865.
- Post-award: Integrate the education with research (CHE 440/450 Chemical Engineering Laboratory)



Next Steps/Long-Term Plans

• Seek collaborations in the microfluidics and renewable energy





2205

Fig. 1. Schematic of a Steam methane reforming (SMR) plant for hydrogen production:, air; ____, CH4; ----H2; ____, exhaust gases; - syngas; - - -, water.

<u>** Lo Lab @ CSULB **</u> <u>https://www.csulb.edu/college-of-engineering/dr-roger-c-lo</u> <u>http://www.microfluidics-at-the-beach.net</u>



Questions?

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Multi-robot Exploration of Spatial-temporal Varying Fields

Wencen Wu – San Jose State University

Wencen Wu, Associate Professor

San Jose State University, Computer Engineering Department

wencen.wu@sjsu.edu



Environmental Disasters



Forest fires

Gas leak

Air crash

Difficult and **dangerous** for people to search and rescue How to explore fields and events in an unknown space?

Problem Formulation

SJSU SAN JOSÉ STATE UNIVERSITY

Employ multi-robot systems to perform exploration tasks for safety and efficiency

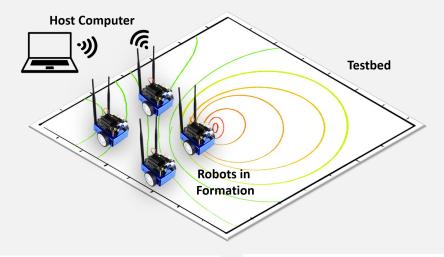
- Source seeking
- Boundary tracking
- Environment mapping

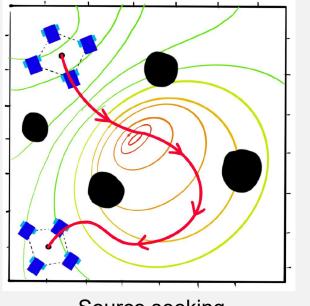
• .

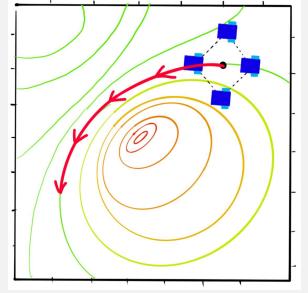
Consider a concentration field z(r). Employ a group of mobile sensors in this field with noisy discrete measurements

 $p(r_{i,k},k) = z(r_{i,k},k) + n_i$

at time step t_k for agent *i* at $r_{i,k}$, i = 1, ..., N





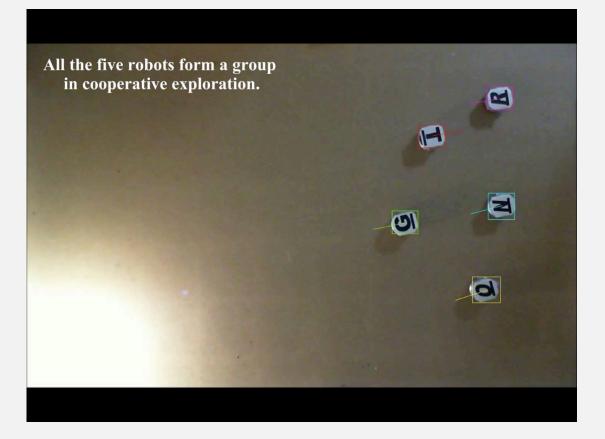


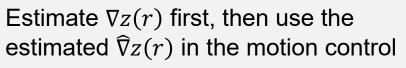
Source seeking

Boundary tracking



Gradient-based vs. Gradient-free Source Seeking







No explicit gradient estimation needed



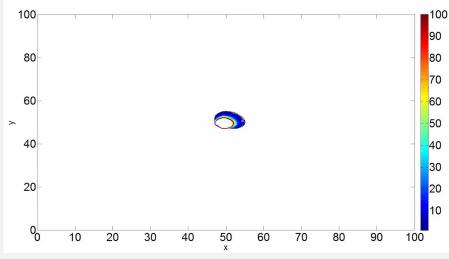
Exploring Spatial-Temporal Varying Fields

Challenges

- Unknown distributed parameters
- Spatial-temporal varying state

 $\frac{\partial z(r,t)}{\partial t} = \sum_{i=1}^{M} \underbrace{\theta_i(t)\psi_i(z(r,t), \nabla z(r,t), \nabla^2 z(r,t))}_{\text{to be estimated}}, \quad r \in \mathbb{R}^d, t \in \mathbb{R}_+$

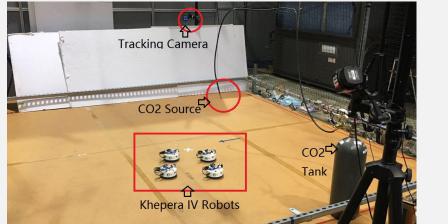
- Goal: using a mobile sensor network to achieve
- state estimation
- parameter identification
- map reconstruction





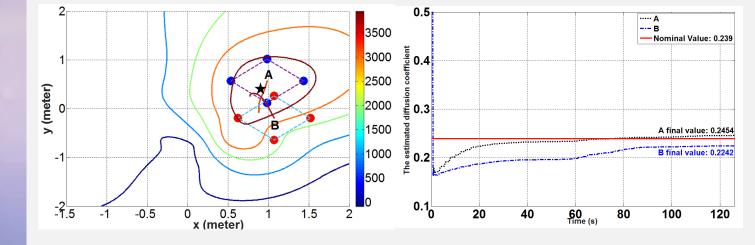
Experimental Results: On-line Parameter Identification

Diffusion Coefficient Identification Using a Multi-Robot System





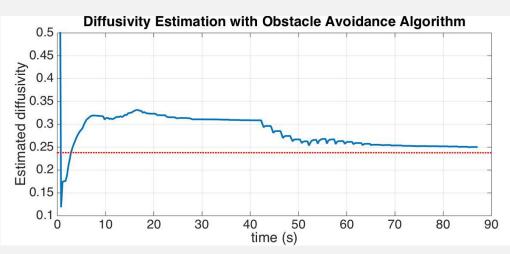
Rensselaer Polytechnic Institute

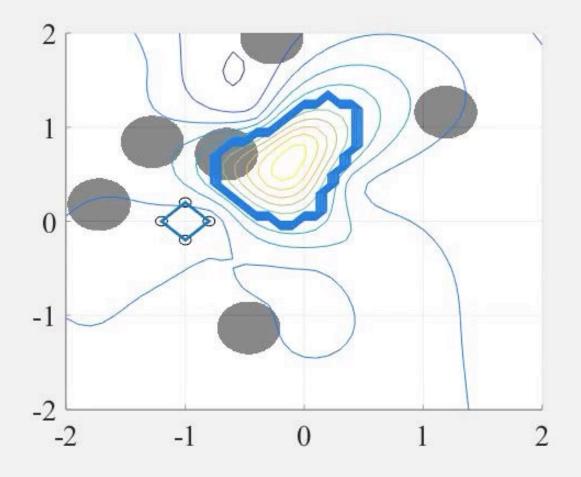




Simulation Study

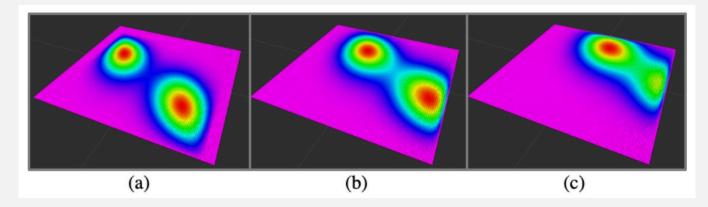
- Consider the field contains
 - Obstacles
 - Hazard zones
- Online parameter identification
 - + state estimation
 - + source seeking





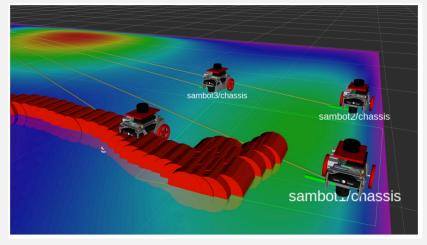


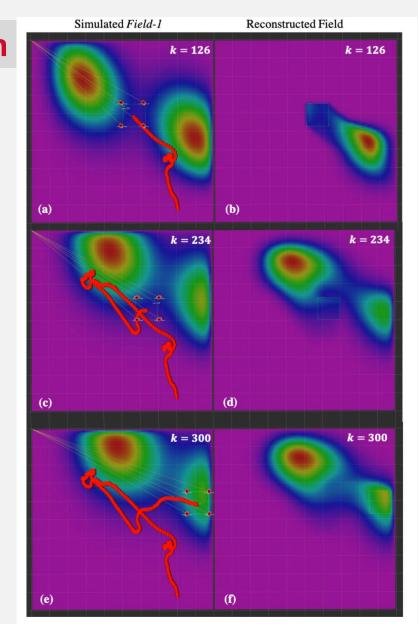
RL Based Path Planning and Field Reconstruction



Representation of an advection-diffusion field grid map in Rviz at 3 time steps.

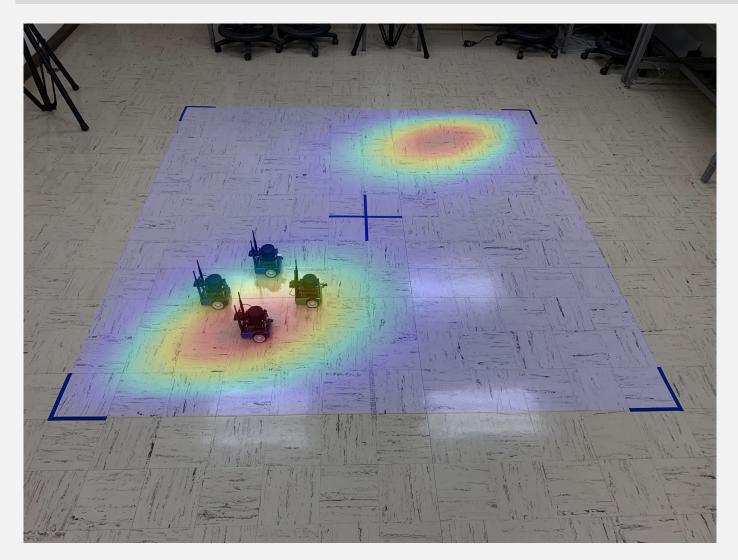
Snapshot of the mobile robot formation moving in the simulated advectiondiffusion field

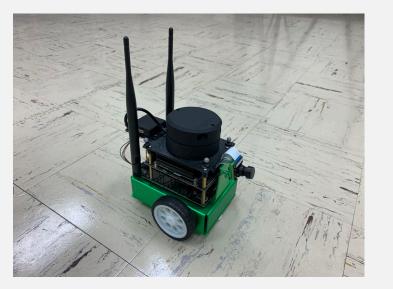


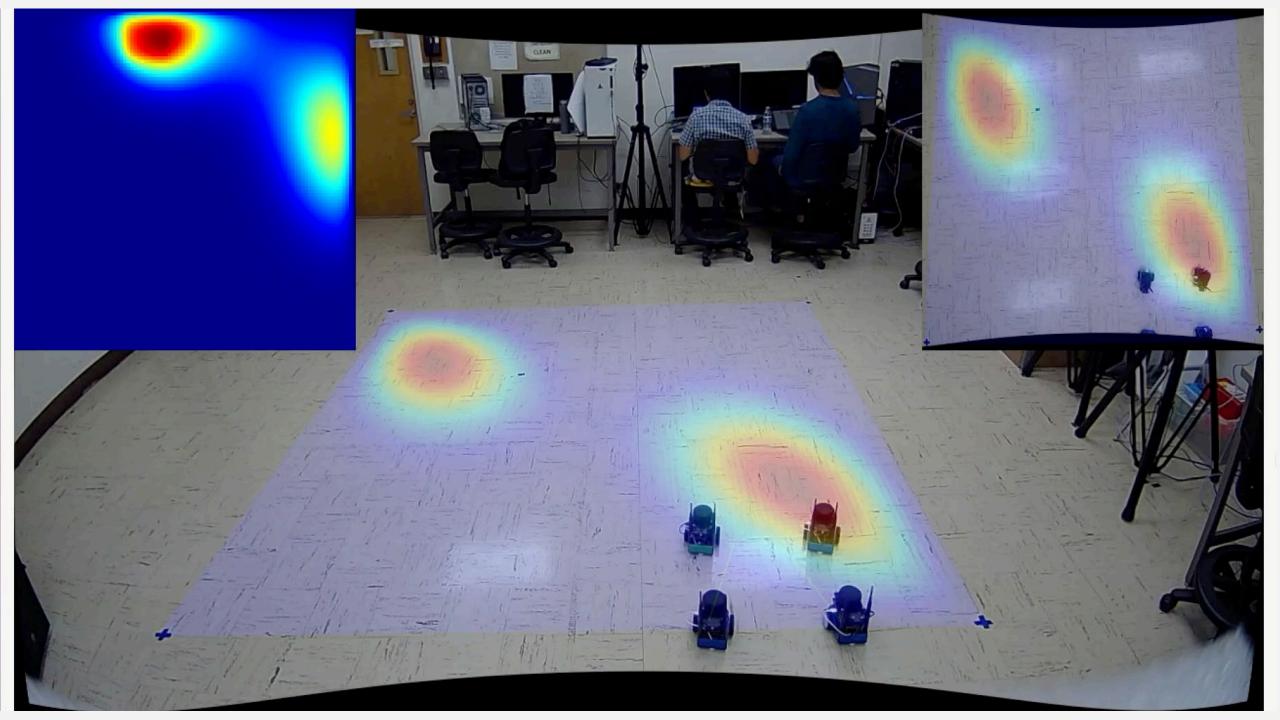




Experimental Study

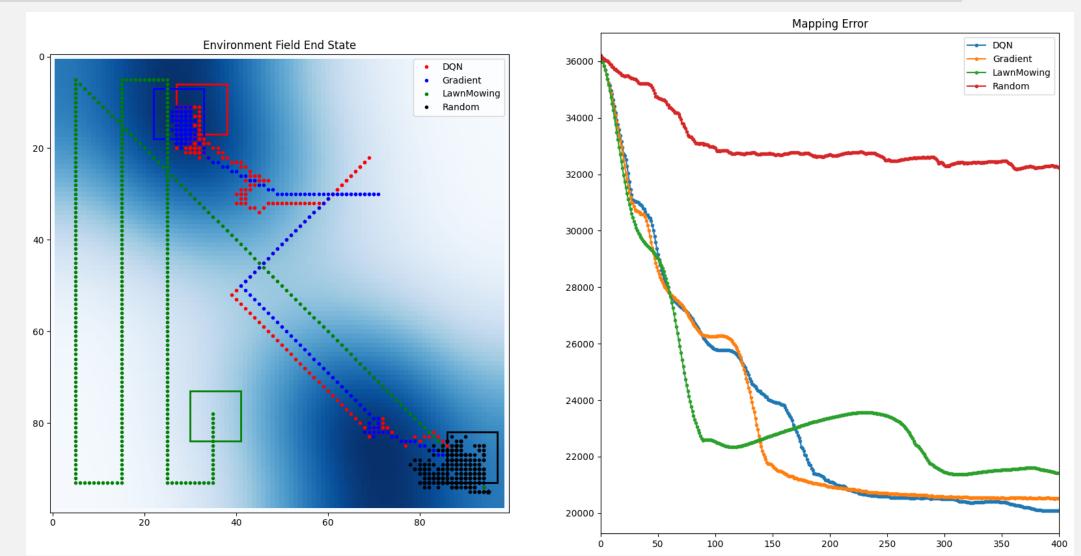








Experimental Study – Comparison with Different Trajectories





Questions?

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Acknowledgement: the research work is supported by NSF grants CPS-1446561, CMMI-1663073, CMMI-1917300, and RINGs-2148353



Experimental Characterization and Computer Vision–Assisted Detection of Pitting Corrosion on Stainless Steel

CALIFORNIA POLYTECHNIC STATE UNIVERSITY, SAN LUIS OBISPO

Dr. Long Wang

Department of Civil and Environmental Engineering California Polytechnic State University, San Luis Obispo

E-mail: lwang38@calpoly.edu

CSU Exemplars in Engineering

October 4, 2023

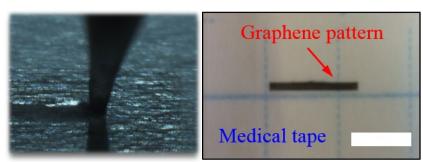
Research Overview



Multifunctional Material Design

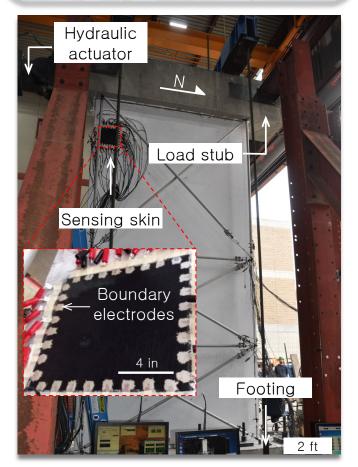


Spray coating of carbon nanotube films

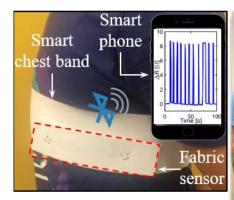


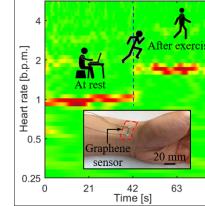
Printing of graphene patterns

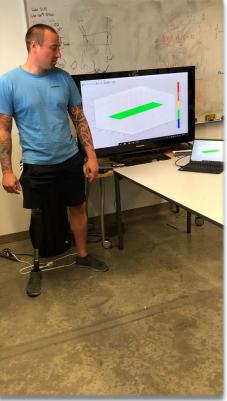
Infrastructure Monitoring





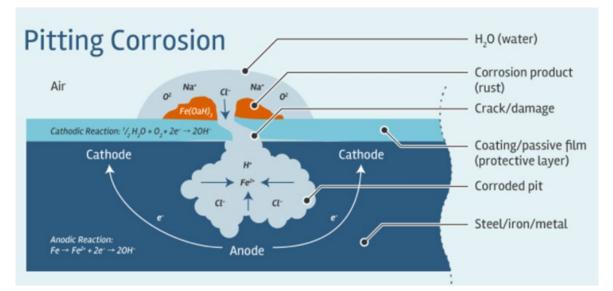




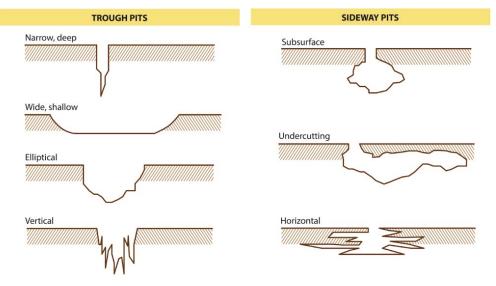




- Pitting damage can potentially lead to structural failure.
 - Failure occurs at the largest defect on the surface, and cannot be equated wholly to mass loss of external topography
 - Fracture mode can change to stress corrosion cracking, a non-ductile, rupture failure for members under tension stress
- It is challenging to identify, predict, and design against (bypasses corrosion resistance) pitting corrosion.



Schematics of pitting corrosion (Source: D&D Coating Ltd)



Common forms of corrosion pit morphologies (Source: AMARINE)

- Various types of structures can be subjected to pitting corrosion.
 - * Examples include bridges, metal pipes, aircrafts, and so forth.



Pitting corrosion on Nandu River Iron Bridge truss member (left), St. Lawrence Seaway Navigation Lock vinyl wall system (middle), and skin plate provided by US Army Corps of Engineers (right)

Existing Technologies for Pitting Corrosion Analysis



| Existing Technology | Pros | Cons | <u>A</u> <u>B</u> <u>C</u> DENSITY <u>SIZE</u> DEPTH |
|------------------------|---|---|---|
| Visual Examination | No technology required | Highly time consuming Difficult if the area is hard to access (i.e., underwater) Subject to human error | 1 \therefore $.$ $.$ $.$ $.$ $.$ $.$ $.$ $.$ $.$ $.$ $.$ |
| Metal Penetration | Cheap technology | Large error in identifying the deepest pits (i.e., largest pit may not be deepest pit especially for loaded members) | 2 $\cdot \cdot \cdot$ |
| Eddy Current | Great accuracy using commercial technology | Expensive Commercial products designed for specific applications such as pipes | 3 $5 \times 10^4/m^2$ 8.0 mm ² 1.6 mm |
| Ultrasound | Good sensitivity for pitting corrosion | Expensive Affected by liquid loading, coatings, and welds Reference standards and large amount of training and experience is required | 4 $1 \times 10^{5}/m^{2}$ 12.5 mm ² 3.2 mm 5 $1 \times 10^{5}/m^{2}$ |
| Profilometry | High accuracy Outputs large amount of useful surface morphology data | Very expensiveUnable to be taken into the field | 5 × 10 ⁵ /m ² 24.5 mm ² 6.4 mm Standard rating chart for pitting corrosion (Source: ASTM G46-21) |



Materials

- \Rightarrow AISI 304 Stainless Steel (50.8 \times 63.5 \times 4.7625 mm³) \Rightarrow Sandpaper
- Iron (III) Chloride *
- Deionized (DI) Water
- Hot Plate / Stir Plate
- 500 mL Beaker

Procedures

- 1. FeCl₃ solution was prepared by dissolving 16.22 g of FeCl₃ powders in 200 mL of deionized (DI) water through stirring and was heated to 50°C.
- 2. Steel specimens were sanded to remove the surficial protective oxide layers and wash with DI water.
- 3. The specimens were then submerged in the solution for a desired timeframe (i.e., 1, 2, 3 hr).
- 4. Once the desired timeframe was reached, the specimens were thoroughly washed with DI water and air dried for at least a day.

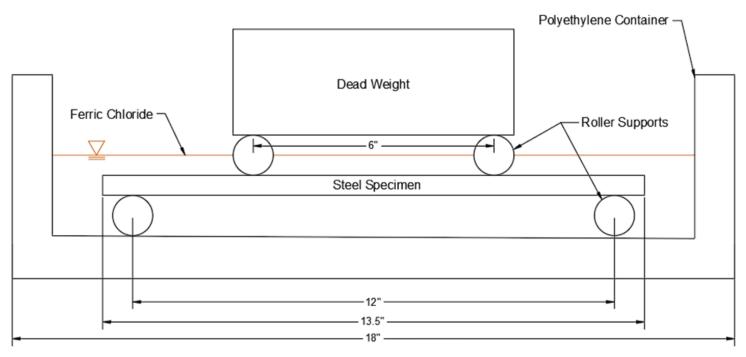
- Sodium Bicarbonate
- Glass Thermometer
- pH Test Strips *



Beaker containing heated ferric chloride and a pitted steel specimen

Procedures

- 1. The 0.5M FeCl₃ corrosive solution and steel specimens (50.8 × 342.9 × 4.7625 mm³) were prepared following the same procedures as the corrosion experiment.
- 2. Each steel specimen was submerged in the corrosive solution and subjected to a four-point bending load simultaneously, generating 28 MPa max stress.
- 3. Once the desired timeframe was reached (i.e., 1, 2, 3 hr), specimens were washed thoroughly with DI water and air dried for at least a day.

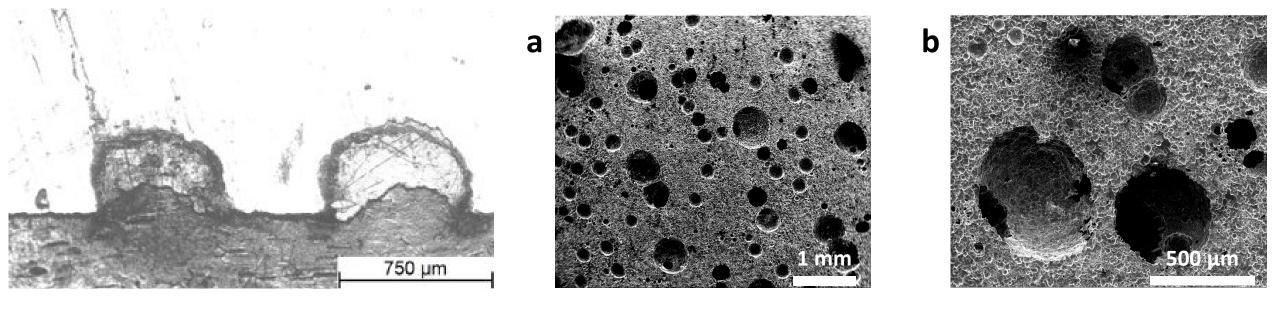




Schematics (left) and an optical image of the experimental setup for the load-coupled corrosion test

Microscopic Imaging of Pits

- Both optical microscopy and scanning electron microscopy (SEM) have been used to characterize microscale pit morphology
 - While microscopic imaging enabled detailed observation of the pits developed at different stages, it was challenging to perform scalable characterization.



Optical image of the cross-sectional view at 50x magnification

SEM images of pits after a three-hour accelerated corrosion experiment

Pit Morphology Characterization

- All specimens were inspected using a Micro Vu Vertex system equipped with an LSM4-2 laser distance scanner.
 - The resolutions were 4 microns and 0.03 microns along x and y directions, respectively.
- Python codes were developed for processing and visualizing the data (3D coordinates for about 2 million data points per scan).
 - The code locally adjusts the surface plane by calculating local neutral axis and shifting nearby points to zero height.
 - ✤ A pit is classified as having eight points in proximity that all fall below the surface threshold.



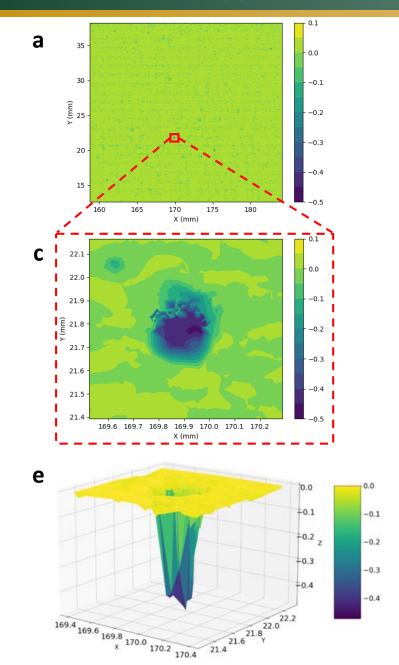
Micro Vu Vertex system with a laser distance scanner during scan of load-coupled specimen



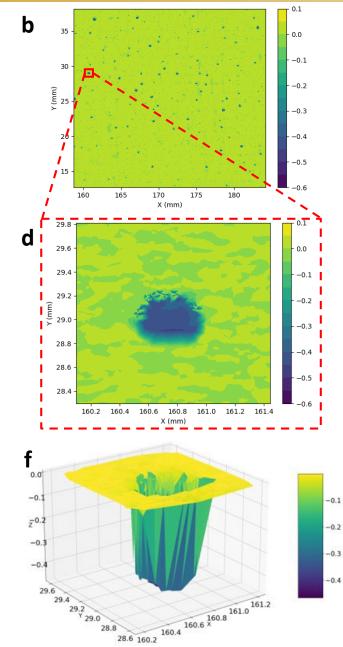


Pit Morphology – 2D and 3D Contours





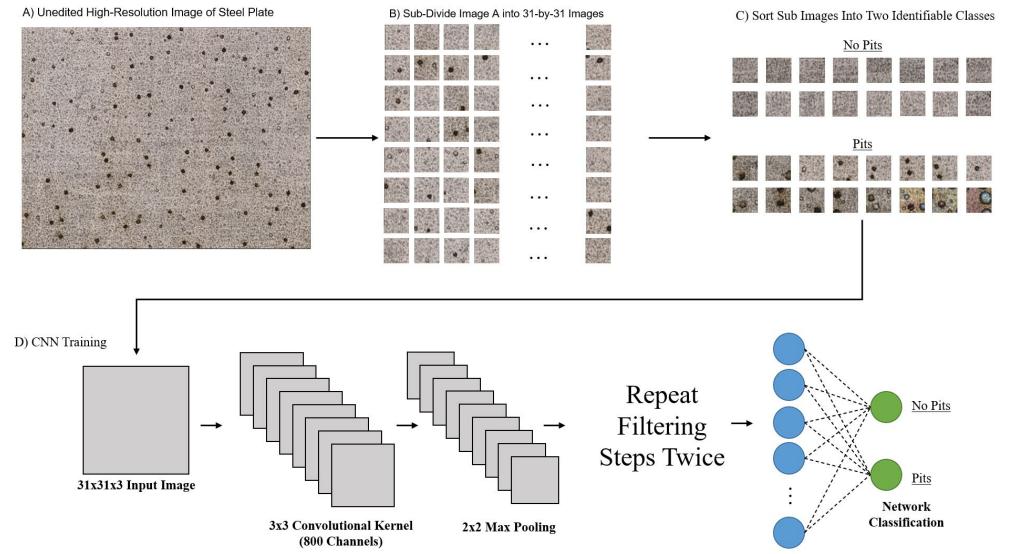
21.4



Color contour plots of 25.4 \times 25.4 mm² central regions on the a) tension and b) compression sides of a steel specimen subjected to 3-hr of load-coupled corrosion experiment. c) and d) Zoomed-in views of individual pits highlighted in a) and b), respectively. e) and f) Visualization of 3D morphologies of pits shown in c) and d), respectively.

Computer Vision Technique

 To detect pit damage in a more efficient and scalable manner, a convolutional neural network (CNN)based computer vision technique was implemented to inspect optical images of steel specimens.



5.12e8 Network Inputs

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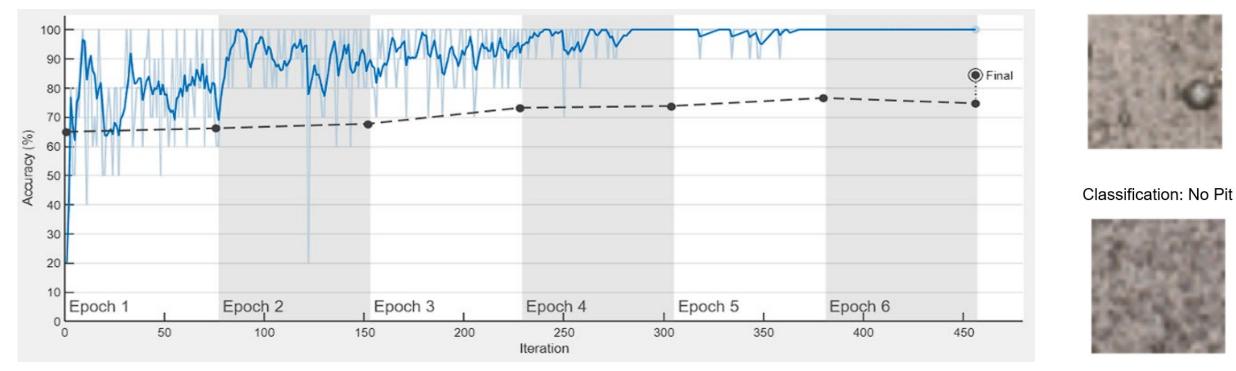
Training CNN



- * "Pit" consists of 740 images
- ^o 70% of the images in each class were used for training and 30% are used for validation.
- Training augmentations that limit the CNN from memorizing the training data include:
 - Randomly reflecting the images horizontally and vertically
 - Randomly translating the image up to 30 pixels horizontally and vertically
- The CNN was trained with a learning rate of 0.0003 over six epochs.
 - To prevent overfitting that would occur at large epochs due to the limited library size

CNN Performance – Accuracy

- The final classification accuracy was 84.45%.
 - * Further training (i.e., more epochs) would lead to overfitting.



Accuracy plot during training with blue line showing the smoothed training accuracy and black line showing validation accuracy at the end of each iteration for MATLAB-based CNN (left) and examples of validation outputs of the trained MATLAB-based CNN algorithm (right)

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Acknowledgements/Questions

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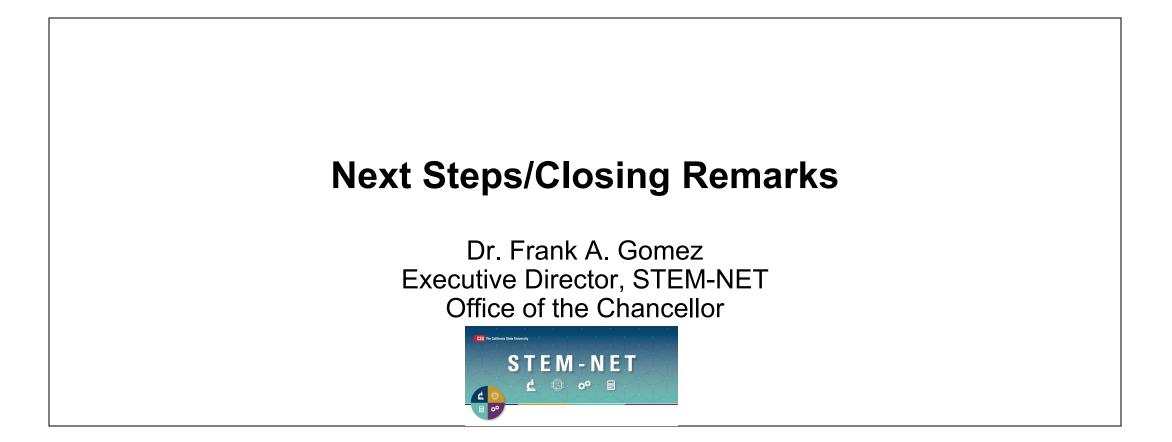








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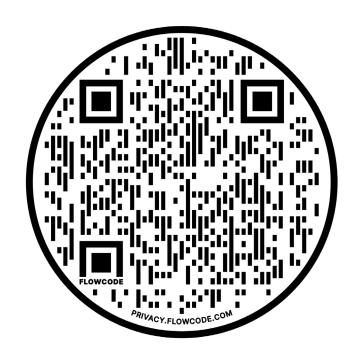
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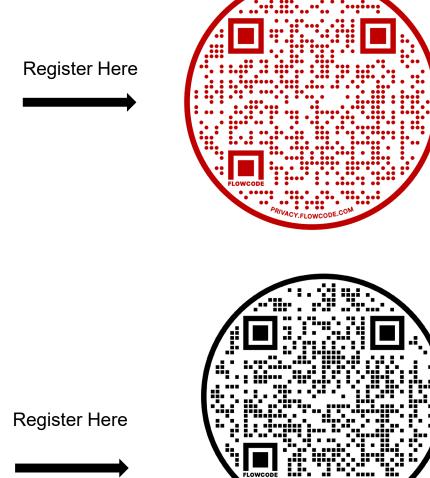
STEM-NET Community Events

STEM-NET Virtual Research Café 10.0

Date: Wednesday, October 18, 2023 Time: 11am-12pm

STEM-NET November Webcast

Topic: NSF CAREER Awardees Date: Wednesday, November 1, 2023 Time: 10am-12pm









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