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
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 Materials

Advancing Mechanics

and

Broadening Participation in Engineering

Underrepresented minorities and women
EML focuses on lightweight and multifunctional materials

**Polymers**
Response of dense and foam polymers to extreme loading scenarios in harsh operating conditions

- Physical
- Mechanical
- Thermal
- Dynamic

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

- Robotic 3D printing
- Terahertz NDE
- Data-driven detection

**Multifunctional**
Strategically leverage solid and structural mechanics to inspire multi-functionality

- Load Management
- Heat Management
- Fluid Management
- Electrical Management
Multiscale Spatiotemporal Investigations

Polymers Science

- Synthesis
- Chemistry
- Physics

Polymers Engineering

- Design
- Manufacturing
- Mechanics

- Optical properties
- Chemical properties
- Electrical properties
- Mechanical properties
- Thermal properties
- Environmental properties
- Physical properties
Polyurea (Model Material System)

- Formed by poly-addition polycarbodiimide-modified diphenylmethane diisocyanate (isocyanate) & poly(tetramethyleneoxide)-di-p-aminobenzoate (diamine)


Mechanically Stronger

Hydrogen bond

Urea linkage

Topography Phase scan

Segmental Microstructure with different mechanical behavior

Steel armor plate without protective coating

Steel armor plate with polyurea protective coating
Full-field Creep Results

DIC Analysis (Vic 2D, Correlated Solutions Inc):
Subset size = 41 pixels (214 µm) - Step size = 10 pixels (52 µm) - Strain filter size = 5

Huynh et al., Macromolecular Rapid Communications (2023)
THz-TDS Results – Time Domain

- Huynh et al., Macromolecular Rapid Communications (2023)
Advancing Mechanics
and
Broadening Participation in Engineering

gyoussef@sdsu.edu
CISE-MSI: Towards Efficient, Reliable, and Secure Chaotic Communications In Wearable Devices

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

Collaborators:
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Ava Hedayatipour, Assistant Professor
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Email: ava.hedayatipour@csulb.edu
Project Overview

Convenience or Complexity?

Sleep Tracker
Smart Coffee Maker
Smart Refrigerator
Cloud Storages
Fitness Tracker
Smart Phones/Watches
Video Conference Rooms
Autonomous Cars
Smart Home Appliances

These are the bulk images taken from google, no copyrights on any of the images.
Project Overview

Internet of Medical Things (IoMT)

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

GROWTH PREDICTION IN IMPLANTABLE/WEARABLE DEVICES’ INDUSTRY

- Market size
- Expon. (Market size)

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 and Purpose

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced encryption standard (AES)</td>
<td>Confidentiality</td>
</tr>
<tr>
<td>Rivest Shamir Adelman (RSA)/ Elliptic Curve Cryptography (ECC)</td>
<td>Digital signatures key transport</td>
</tr>
<tr>
<td>Diffie-Hellman (DH)</td>
<td>Key agreement</td>
</tr>
<tr>
<td>SHA-1/SHA-256</td>
<td>Integrality</td>
</tr>
</tbody>
</table>
CISE-MSI: Towards Efficient, Reliable, and Secure Chaotic Communications In Wearable Devices

Project Overview

Message → Encryption → Cipher Text → Decryption → Message

Public Key

Secret Key

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

Project Overview

**Phase 1:** Transmitter and receiver design based on different chaotic equations for communication

- Lorenz equations chaotic circuit
- Modified Lorenz equations chaotic circuit
- Chuya’s equations chaotic circuit

**Outcome:** A Chaotic transmitter and receiver circuit capable of real-time ciphering of the data

- Sensor data
- Transmitter circuit based on chaotic equations
- Ciphered signal through public channel
- Chaotic circuit based on chaotic equations
- Deciphered sensor data

**Phase 2:** Provably secure logic locking for chaotic communication

- Sensor data
- Original Transmitter (or Receiver) \( f(Data) \)
- Locked Transmitter (or Receiver) \( g(Data, Key) \)

\[ f(Data) = g(Data, K^*) \]

Original transmitter (or receiver) and locked transmitter (or receiver) are equivalent under correct key \( K^* \).

**Outcome:** A secure and digitally locked transmitter and receiver design

- Sensor data
- Transmitter with digital locking
- Ciphered signal through public channel
- Chaotic receiver with digital locking
- Deciphered sensor data

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

**Project Overview**

**Phase 3: Efficient machine learning algorithms for reliable chaotic encryption**
- Deciphered sensor data
- Data Preprocessing → Feature Selection → ML Implementation
  - Identify the most important features
  - Train and test various ML classifiers (Decision Tree, Random Forest, Regression, Deep Learning, etc.)
- Identify the most accurate and cost-effective ML

**Outcome: A digitally locked transmitter and receiver optimized with machine learning algorithms**
- Sensor data → Transmitter with digital locking → Ciphered signal → Chaotic receiver with digital locking → Deciphered sensor data → Accurate and cost-effective machine learning algorithms
  - Key input

**Phase 4 design and outcome: Chip implementation of the reliable and secure chaotic circuit**
- Sensor data → Transmitter and receiver implemented as an integrated chip → Deciphered sensor data → Accurate and cost-effective machine learning algorithms
  - Key input
Results

- Demonstration of encryption architecture on Xilinx’s Digilent Artix7 Nexys7 FPGA board.
- The JTAG port has been used to deliver the computation to the board and bring back the results.

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

Summary

Sensor data

Sensor

Chaotic transmitter with digital locking

Ciphered signal through public channel

Chaotic receiver with digital locking

Deciphered sensor data

Smart machine learning algorithm as a dynamic feedback
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)

\[
\min_{x,y} c^T x \\
\text{s.t. } \begin{cases} F(x, y) \leq d, \\ \mathbb{P}(\theta^T x \leq b) \geq 0.95 \end{cases} \\
x \in \mathbb{R}, y \in \{0,1\}.
\]

Random Algorithm: Scenario Approximation, Scenario Tree

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

• Data-Driven Modeling and Global Optimization

Gaussian Mixture Model (GMM)

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

- Develop GMM-based CCP
- Oil Blending Experiment
- Two-stage CCP with line decision rule
- Two-stage CCP with piecewise decision rule
- Collaboration & new proposal submission

- Oil blending modeling and optimization
- Generate an edible oil blending dataset
- Refinery optimization
- Refinery optimization
- Target: NSF, DOE
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%)

<table>
<thead>
<tr>
<th></th>
<th>GMM-CCP</th>
<th>Scenario Average (SA)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit</td>
<td>$378.49</td>
<td>$354.60</td>
</tr>
<tr>
<td>Solution time</td>
<td>6,668 s</td>
<td>101 s</td>
</tr>
<tr>
<td>Conclusion</td>
<td>Slow but guaranteed optimality</td>
<td>Fast but needs significant tuning</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th></th>
<th>GMM-CCP + Decision-Rule</th>
<th>Scenario Tree</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Profit:</strong></td>
<td>$102,467,704</td>
<td>$101,282,597</td>
</tr>
<tr>
<td><strong>Solution time:</strong></td>
<td>4709 s</td>
<td>7224 s</td>
</tr>
<tr>
<td><strong>Risk:</strong></td>
<td>2.4%&lt;5%</td>
<td>2%&lt;5%</td>
</tr>
<tr>
<td><strong>Conclusion:</strong></td>
<td>Faster, Scalable, More profitable</td>
<td>Slower, Non-scalable</td>
</tr>
</tbody>
</table>
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.

• 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

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

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Multi-robot Exploration of Spatial-temporal Varying Fields

Wencen Wu – San Jose State University

Wencen Wu, Associate Professor
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Environmental Disasters

Difficult and dangerous for people to search and rescue

How to explore fields and events in an unknown space?
Problem Formulation

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 $r_{i,k}$, $i = 1, ..., N$
Gradient-based vs. Gradient-free Source Seeking

All the five robots form a group in cooperative exploration.

Estimate $\nabla z(r)$ first, then use the estimated $\hat{\nabla} z(r)$ in the motion control.

No explicit gradient estimation needed.
Exploring Spatial-Temporal Varying Fields

Challenges

• Unknown distributed parameters
• Spatial-temporal varying state

\[ \frac{\partial z(r, t)}{\partial t} = \sum_{i=1}^{M} \theta_i(t) \psi_i(z(r, t), \nabla z(r, t), \nabla^2 z(r, t)), \quad r \in \mathbb{R}^d, t \in \mathbb{R}_+ \]

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

Multi-robot Exploration of Spatial-temporal Varying Fields
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 advection-diffusion field.
Experimental Study

Multi-robot Exploration of Spatial-temporal Varying Fields
Experimental Study – Comparison with Different Trajectories

Multi-robot Exploration of Spatial-temporal Varying Fields
Questions?

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

Dr. Long Wang

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CSU Exemplars in Engineering
October 4, 2023
Research Overview

Multifunctional Material Design

Infrastructure Monitoring

Human Monitoring

Spray coating of carbon nanotube films

Graphene pattern

Medical tape

Printing of graphene patterns

Hydraulic actuator

Load stub

Sensing skin

Boundary electrodes

Footing

Smart chest band

Smart phone

Fabric sensor

Heart rate (b.p.m.)

Time [s]
Pitting corrosion is a type of localized corrosion that is both autocatalytic and irregular, creating cavities within a material.

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.
Various types of structures can be subjected to pitting corrosion.

- Examples include bridges, metal pipes, aircrafts, and so forth.
## Existing Technologies for Pitting Corrosion Analysis

<table>
<thead>
<tr>
<th>Existing Technology</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual Examination</td>
<td>• No technology required</td>
<td>• Highly time consuming</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Difficult if the area is hard to access (i.e., underwater)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Subject to human error</td>
</tr>
<tr>
<td>Metal Penetration</td>
<td>• Cheap technology</td>
<td>• Large error in identifying the deepest pits (i.e., largest pit may not be deepest pit especially for loaded members)</td>
</tr>
<tr>
<td>Eddy Current</td>
<td>• Great accuracy using</td>
<td>• Expensive</td>
</tr>
<tr>
<td></td>
<td>commercial technology</td>
<td>• Commercial products designed for specific applications such as pipes</td>
</tr>
<tr>
<td>Ultrasound</td>
<td>• Good sensitivity for pitting</td>
<td>• Expensive</td>
</tr>
<tr>
<td></td>
<td>corrosion</td>
<td>• Affected by liquid loading, coatings, and welds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Reference standards and large amount of training and experience is</td>
</tr>
<tr>
<td></td>
<td></td>
<td>required</td>
</tr>
<tr>
<td>Profilometry</td>
<td>• High accuracy</td>
<td>• Very expensive</td>
</tr>
<tr>
<td></td>
<td>• Outputs large amount of</td>
<td>• Unable to be taken into the field</td>
</tr>
<tr>
<td></td>
<td>useful surface morphology</td>
<td></td>
</tr>
</tbody>
</table>

### Standard rating chart for pitting corrosion

(Source: ASTM G46–21)
Accelerated Pitting Corrosion Experiment

- **Materials**
  - AISI 304 Stainless Steel (50.8 × 63.5 × 4.7625 mm³)
  - Iron (III) Chloride
  - Deionized (DI) Water
  - Hot Plate / Stir Plate
  - 500 mL Beaker
  - Sandpaper
  - Sodium Bicarbonate
  - Glass Thermometer
  - pH Test Strips

- **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.
Load-Coupled Corrosion Experiment

- **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
Both optical microscopy and scanning electron microscopy (SEM) have been used to characterize micro-scale 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
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.
Pit Morphology – 2D and 3D Contours

Color contour plots of 25.4 × 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.
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.
An image library was established by partitioning 443×340-pixel images into smaller 31×31-pixel sub-images for training and testing the CNN. The training library included two classes:

- “Pit” – consists of 740 images
- “No Pit” – consists of 353 images

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
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).
Acknowledgements/Questions

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Duncan Fure, Civil
Marina Wong, Materials
Riley Muehler, Civil (Graduated)
Josh Venz, Materials (Graduated)

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U.S. National Science Foundation (NSF)

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Next Steps/Closing Remarks

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Executive Director, STEM-NET
Office of the Chancellor

https://www2.calstate.edu/impact-of-the-csu/research/stem-net
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STEM-NET November Webcast
Topic: NSF CAREER Awardees
Date: Wednesday, November 1, 2023
Time: 10am-12pm

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