# DIRAS: Distributed Image Reconstruction in Adversarial Scenario Under the supervision of Prof. Sanand Dilip Amita Athalye

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# **Motivation**

➤ CyberPhysical Systems (CPSs) - Integrate features physical processes with computational processes and communication networks [Baheti and Gill, 2011]

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- Reasons for success of CPS and IoT:
  - ▶ Ability to acquire a large amount of data from various sources
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- Analysis of image plays a key role in agriculture [Vibhute and Bodhe, 2012], medical systems [Dougherty, 2009], remote sensing [Chen, 2012], robotics [Kurka and Salazar, 2019]
- Image data holds great value in numerous fields

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- These issues need to be addressed



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- We propose DIRAS: Distributed Image Reconstruction in Adversarial Scenarios
- DIRAS is distributed which makes it fault-tolerant
- Uses data splitting for improving privacy and efficiency of data sharing
- Uses Robust Principal Component Analysis and Matrix Completion for cleaning the tampered image
- Incorporates other mechanisms to mitigate the effect of other security attacks

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DIRAS combines the concept of security in CPS, distributed optimization and image reconstruction for secure and scalable reconstruction of images.

### Background

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  - ► PCA based on a convex optimization problem called Principal Component Pursuit
- However, in case of gross errors performance of PCA degrades
- ► Need for making PCA robust
- ► RPCA helps in extracting the low-rank matrix and the sparse matrix from the data matrix in case of gross errors



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- Occurs when the node reconstructing the image does not receive chunks of the image - parts of an image are missing
- ► Matrix Completion is used to obtain those parts of the images that have been lost by the framework

### System Design

There are a few assumptions that have been made while designing DIRAS

▶ Monitor nodes (the nodes that process and reconstruct images) are connected over a peer-to-peer network, i.e., every monitor node is connected to another

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- Network is synchronous
- Monitors have enough computation power to run RPCA and matrix completion algorithms
- Sensors have enough computation power to split images into chunks

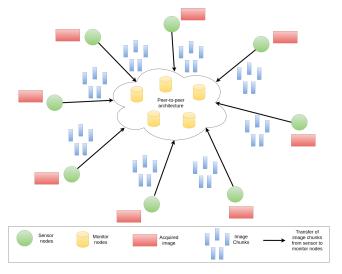


Figure: High level architecture of DIRAS

- Sensor nodes
- Monitor nodes
- ► Peer-to-peer network

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- Sensor nodes
  - Acquire images from surroundings
- Monitor nodes
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- Sensor nodes
  - Acquire images from surroundings
  - Send the images to the monitor nodes for further analysis
- Monitor nodes
- Peer-to-peer network

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- Sensor nodes
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  - Obtain images from the sensors
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- Sensor nodes
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  - Reconstruct the whole image which is used for further analysis
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- Sensor nodes
- Monitor nodes
  - Obtain images from the sensors
  - Reconstruct the whole image which is used for further analysis
  - ▶ Remove the noise added to the image by an attacker
- Peer-to-peer network

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- Peer-to-peer network
  - Monitors are connected over a peer-to-peer network (p2p network)
  - Ensures that a monitor can share packet with any other monitor
  - Reasonable assumption considering the advent of IoT

#### System Design - Functionality

- ► Monitor Position Assignment
- Image acquisition and splitting
- Lightweight Leader Selection Algorithm
- Image Reconstruction
- ▶ Improvement in DIRAS: Load Balancing

We explain each of these steps in the next few slides.

#### System Design - Functionality

- Monitor Position Assignment Occurs every epoch time
   (Δ)
- Image acquisition and splitting
- Lightweight Leader Selection Algorithm
- ► Image Reconstruction
- Improvement in DIRAS: Load Balancing

#### System Design - Functionality

#### **Monitor Position Assignment**

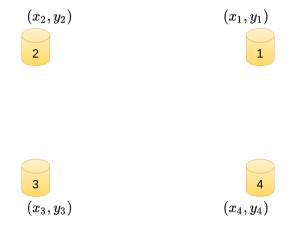


Figure: Monitors generate (pseudo)random coordinates

### **Monitor Position Assignment**

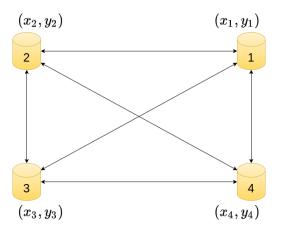


Figure: Monitors broadcast the random coordinates to each other

#### **Monitor Position Assignment**

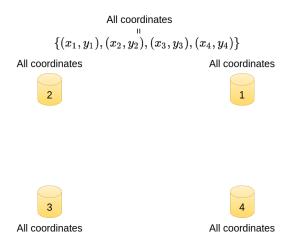


Figure: Monitors acquire and store the coordinates of all other monitors

- ► Monitor Position Assignment
- ► Image acquisition and splitting
- ► Lightweight Leader Selection Algorithm
- Image Reconstruction
- Improvement in DIRAS: Load Balancing

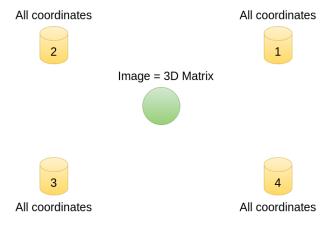


Figure: Sensor acquires image

#### Image acquisition and splitting

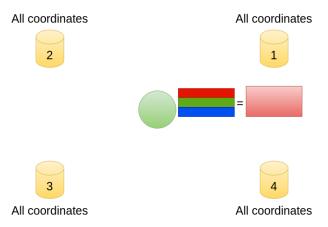


Figure: Sensor stacks the R, G and B components vertically to create a 2-D matrix

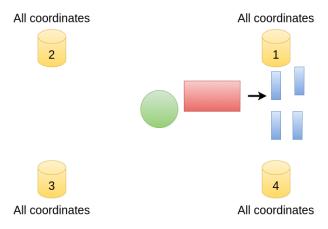


Figure: Sensor splits the image into chunks

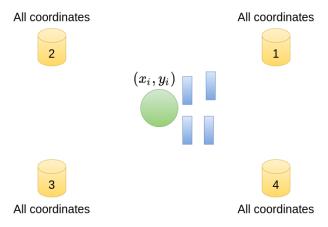


Figure: Sensor generates a random coordinate

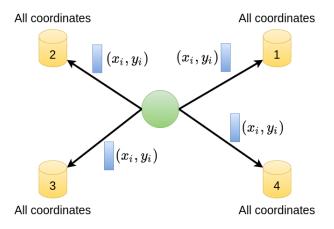


Figure: Sensor sends coordinates and chunks to the monitors

- ► Monitor Position Assignment
- ► Image acquisition and splitting
- Lightweight Leader Selection Algorithm
- Image Reconstruction
- Improvement in DIRAS: Load Balancing

All coordinates

 $(x_i,y_i)$ 

### Lightweight Leader Selection Algorithm

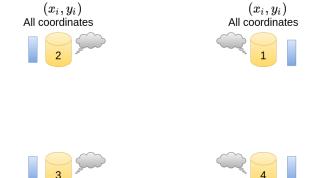


Figure: Monitors find the distance between  $(x_i, y_i)$  and all  $(x_j, y_j)$  using  $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$ , where  $j = \{1, 2, 3, 4\}$ 

All coordinates

 $(x_i,y_i)$ 

### Lightweight Leader Selection Algorithm

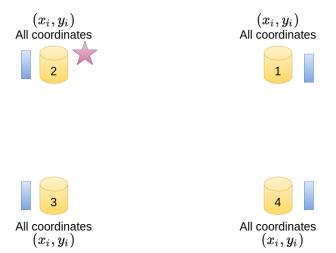


Figure: Monitor with the shortest distance from  $(x_i, y_i)$  is the leader

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- ► Image acquisition and splitting
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#### Image Reconstruction

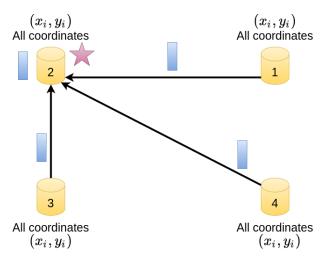


Figure: Monitors send chunks of image to the leader

#### Image Reconstruction

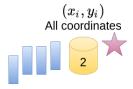








Figure: Leader gets all the chunks from the monitors

#### Image Reconstruction







Figure: Leader combines all the chunks to form a single 2D matrix

#### Image Reconstruction

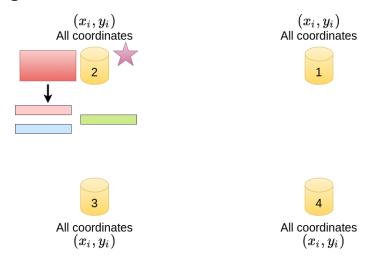


Figure: Leader separates the R, G, and B components of the image

#### Image Reconstruction

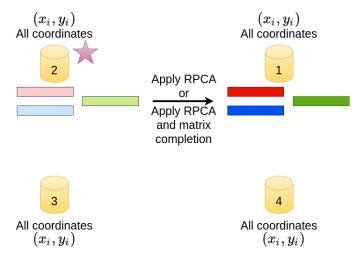


Figure: Leader applies RPCA or RPCA along with matrix completion to remove noise and reconstruct the matrix



#### Image Reconstruction

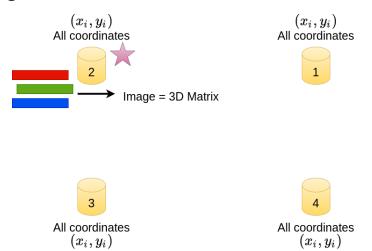


Figure: Leader combines the R, G, and B components of the image to obtain the entire image



### When and why do we need RPCA?

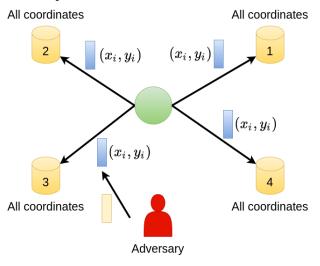


Figure: Attacker adds injects false data to the chunk

# When and why do we need RPCA with matrix completion?

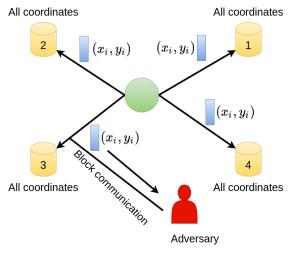


Figure: Attacker adds injects false data to the chunk

- ► Monitor Position Assignment
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### Improvement in DIRAS: Load Balancing

Leader selection algorithm in DIRAS:

$$\begin{split} &L(I_i)=j,\quad \text{s.t.} \quad \min_j \quad D_{ij} \\ &\text{where} \quad D_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}, \quad j=1,..., \textbf{MN} \end{split}$$

### Improvement in DIRAS: Load Balancing

► Leader selection algorithm in DIRAS:

$$\label{eq:Leader} \begin{array}{ll} \textit{Leader} = \textit{j}, & \text{s.t.} & \min_{\textit{j}} & \textit{D}_{\textit{ij}} \\ \\ \text{where} & \textit{D}_{\textit{ij}} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, & \text{j} = 1,..., \textbf{MN} \end{array}$$

 $\triangleright x_i, y_i, x_j, y_j$  are all random numbers

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- Therefore, some monitors will have to reconstruct more images, while some will have to regenerate less images

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- Therefore, some monitors will have to reconstruct more images, while some will have to regenerate less images
- ► Hence, latency will be induced

### Improvement in DIRAS: Load Balancing

► Incorporation of load balancing

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- Incorporation of load balancing
- ► After incorporating load balancing, leader selection algorithm becomes:

Leader 
$$= j$$
, s.t.  $\min_{j} F_{ij}$ 

$$F_{ij} = D_{ij} + \beta_{j} \times \max_{j} D_{ij}$$
where  $D_{ij} = \sqrt{(x_{i}(I_{i}) - x_{j})^{2} + (y_{i}(I_{i}) - y_{j})^{2}}$ ,  $j = 1, ..., MN$ 

 $eta_j$  is the total number of images regenerated by that monitor

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The term  $\beta_j \times \max_j D_{ij}$  ensures that the computation burden is distributed evenly in the monitor node network

# **Implementation**

Done on ns-3 network simulator

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- For evaluation of overheads and delays

# Implementation - Image Reconstruction

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- Apply Matrix Completion with RPCA and measure its performance

#### Implementation - Image Reconstruction

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- Use Euclidean norm to find the similarity between actual and reconstructed matrices

#### Implementation - Image Reconstruction

- ▶ Done on Python (using NumPy and cvxpy)
- Involves reading an image in form of a matrix and adding noise to it
- Apply RPCA and measure its performance
- Apply Matrix Completion with RPCA and measure its performance
- Use Euclidean norm to find the similarity between actual and reconstructed matrices
- ► For studying the performance of image reconstruction

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- ► For studying the amount of information revealed by a given number of rows of a matrix

# **Evaluation**

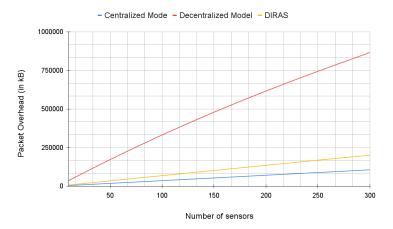


Figure: Variation in packet overhead with change in number of sensor nodes and comparison with centralized and decentralized models

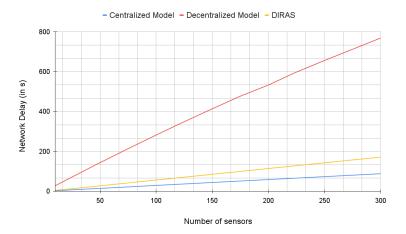


Figure: Variation in delay with change in number of sensor nodes and comparison with centralized and decentralized models

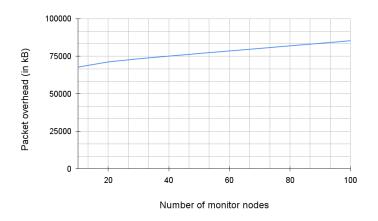


Figure: Variation in packet overhead with change in number of monitor nodes

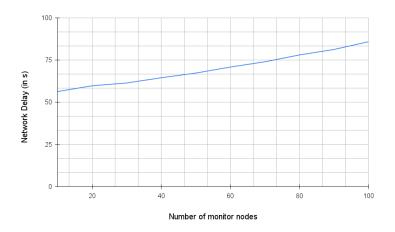


Figure: Variation in delay with change in number of monitor nodes

### **Evaluation - Image Reconstruction**

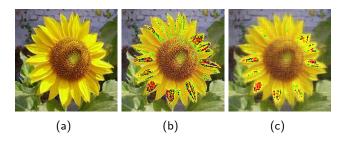


Figure: Denoising by RPCA - (a) Actual Image (b) Image with noise (c) Reconstructed image

#### **Evaluation - Image Reconstruction**

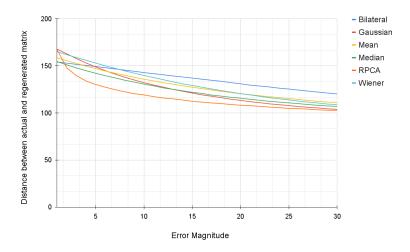


Figure: Performance of DIRAS in case of false data injection and its comparison with other filters

#### **Evaluation - Image Reconstruction**

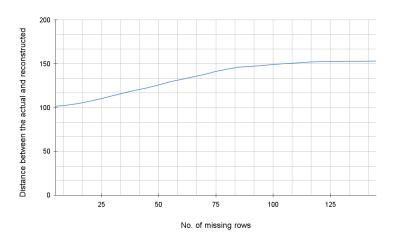


Figure: Performance of DIRAS in case of packet dropping and false data injection

### Evaluation - Load Balancing Analysis

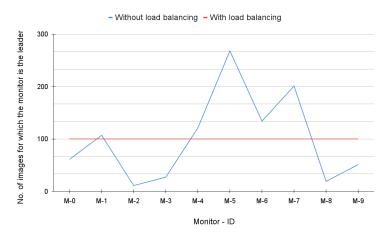


Figure: Improvement in performance because of load balancing based on the number of images for which each monitor node has been chosen as the leader

### Evaluation - Privacy Analysis

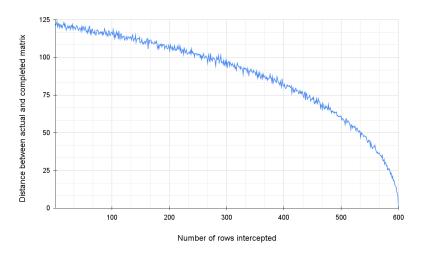


Figure: Privacy provided by DIRAS based on distance between the actual matrix and the matrix reconstructed after applying matrix completion



# Discussion

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- For successfully obtaining substantial information attacker needs to control multiple channels, which is difficult - figure 28
- ➤ To reduce number of rows in a chunk increase the number of monitor nodes this increases the latency and bandwidth a little trade-off between network performance and privacy

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  - lacktriangle Attacker can still cause damage to the network in a  $\Delta$
  - Load balancing helps in resolving this issue

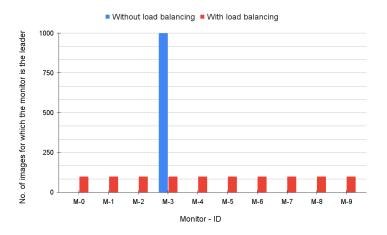


Figure: Mitigation of effect of DoS attacks by load balancing

Some of these work can be considered for the forthcoming semester:

▶ Improving the quality of image obtained after reconstruction

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- Developing a defense mechanism against Sybil attacks [Douceur, 2002]
- Improving the privacy by integrating differential privacy [Dwork, 2008]

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- DIRAS is a novel solution for image reconstruction
- Distributed which makes it scalable
- Provides defense against multiple attacks
- Privacy-preserving
- Image reconstruction part is still not robust needs improvements
- Can be integrated with any system that uses matrix for data storage and processing

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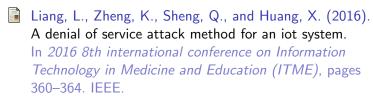
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# Thank You!