MULTI-VIEW FRAME RECONSTRUCTION WITH CONDITIONAL GAN

Tahmida Mahmud, Mohammad Billah, Amit K. Roy-Chowdhury
University of California, Riverside

UCR Bourns College of Engineering
Video Computing Group

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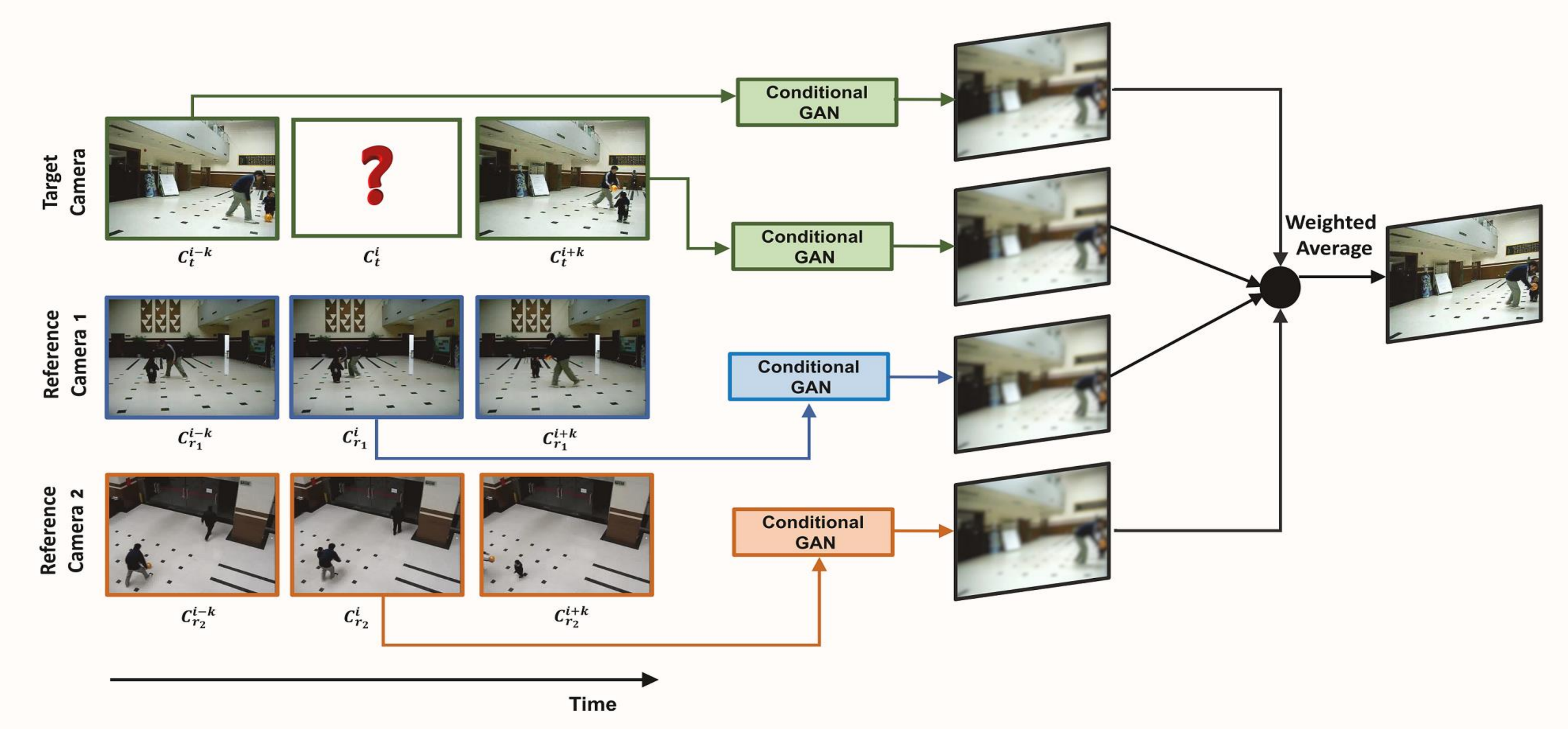
1. Motivation

- Frame reconstruction is critical in applications like retrieving missing frames in surveillance videos, anomaly detection, data compression, video editing, video post-processing, animation, spoofing and so on.
- When multiple frames are missing and adjacent frames within the camera are far apart, realistic coherent frames can still be reconstructed using corresponding frames from other overlapping cameras.

2. Contributions

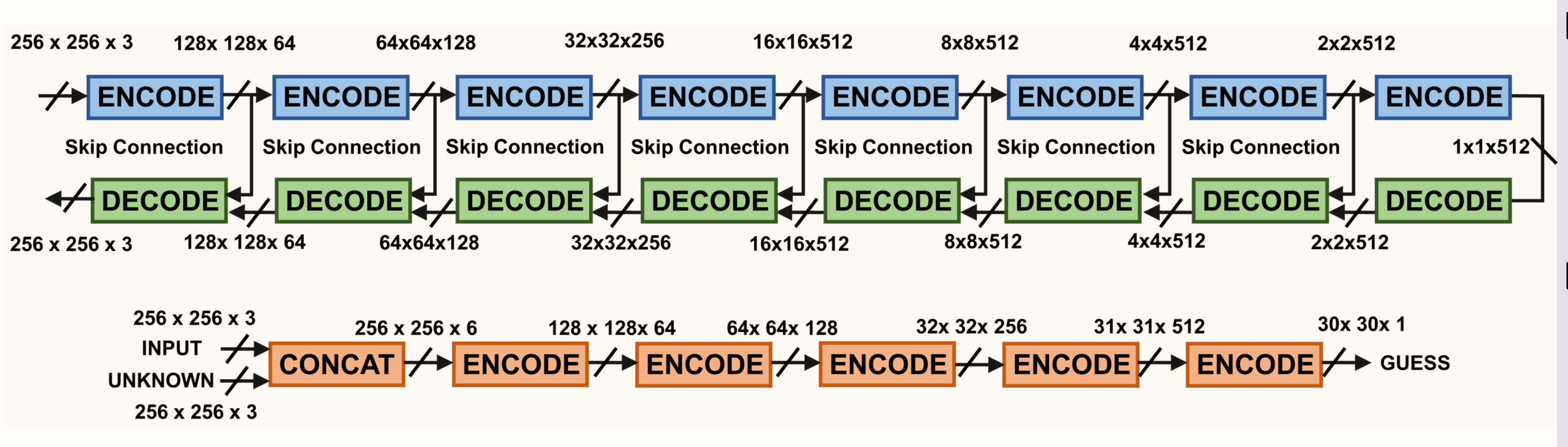
- We tackle a novel problem of frame reconstruction in multi-camera scenario using an adversarial approach.
- We perform extensive experiments on a challenging multi-camera video dataset to show the effectiveness of our method and on a single-camera video dataset to provide quantitative comparison with the state-of-the-art.

3. Solution Overview



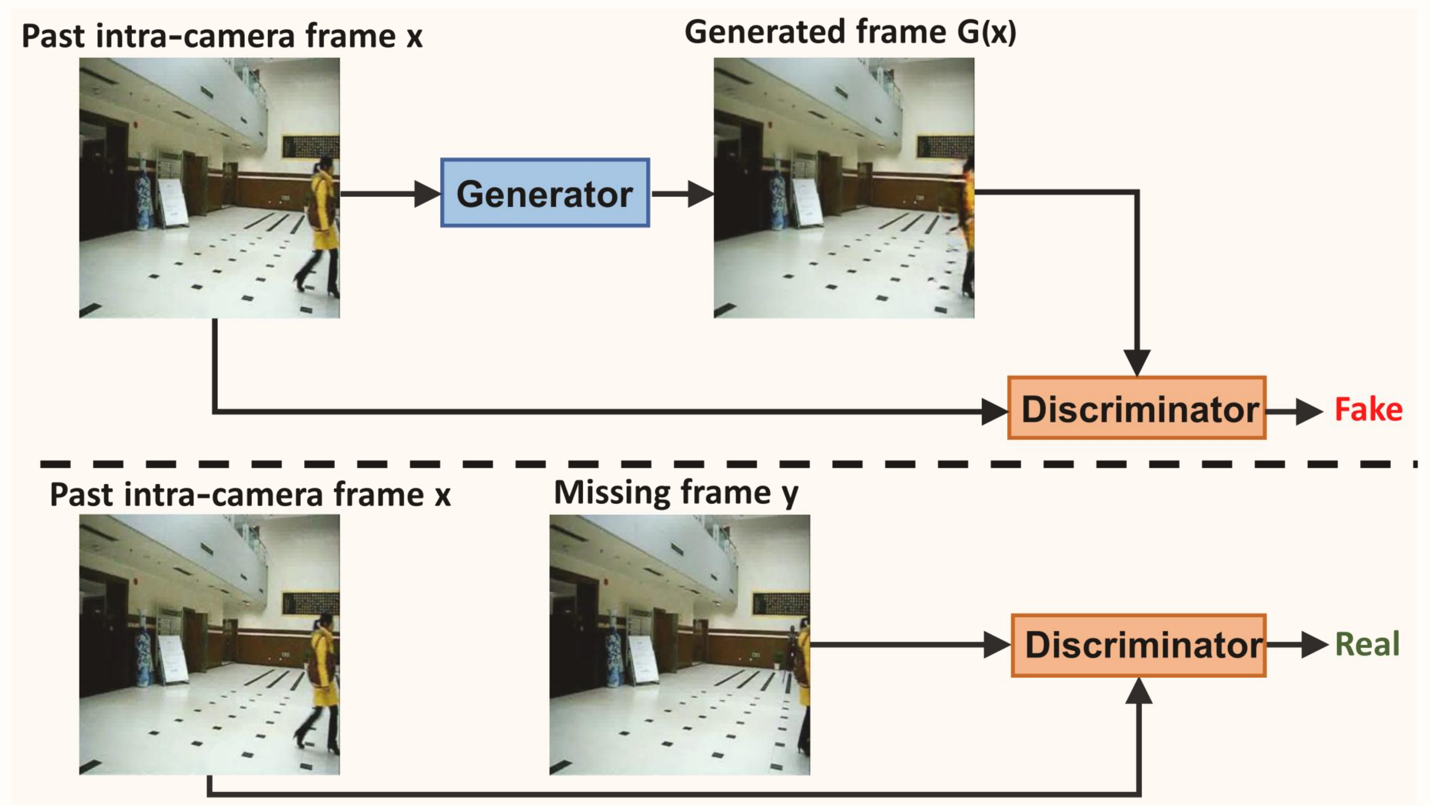
- We learn the representations of the missing frame conditioned on the preceding and following frames within the camera and on the corresponding frames in other overlapping cameras using cGAN.
- These representations are merged together using a weighted average where the weights are chosen by maximizing the average PSNR on a smaller validation set.

4. Network Architecture



- "U-Net"-based architecture of the generator with skip connections which directly connect encoder layers to decoder layers.
- The discriminator tries to differentiate at patch-level and runs convolutationally across the image to generate an averaged output.

5. Model Training Approach



$$G^* = E_{x,y}[\log D(x,y)] + E_{x,z}[\log(1-D(x,G(x,z)))] + \lambda E_{x,y,z}[\|y-G(x,z)\|_1]$$

- We use a combination of $L1$ loss and adversarial loss in the objective function.
- We alternate between a gradient descent step upon D and one upon G and the training maximizes $\log D(x, G(x,z))$.
- To optimize the network, we use a minibatch stochastic gradient descent with an adaptive subgradient method (Adam) and a learning rate of 0.0002.

6. Datasets and Experimental Results

- **KTH Human Action Dataset**: Single-view dataset with 6 types of human activities

Method	PSNR	SSIM
Proposed Method	35.03	0.93
LSTM-Based Method [24]	35.40	0.96

Table 1. Single-view Reconstruction Performance Comparisons for KTH Human Action Dataset.

- **Office Lobby Dataset**: Multi-view dataset with 3 video clips captured by 3 cameras

Gap (frames)	1	3	5	7	15	30
PSNR	32.06	29.28	28.10	27.19	25.56	25.17
SSIM	0.95	0.92	0.91	0.90	0.88	0.87

Table 2. Multi-view Reconstruction Performance for Office Lobby Dataset.

Gap (frames)	1	3	5	7	15	30
Single	32.06	29.24	28.02	27.02	24.17	23.97
Multi	32.06	29.28	28.10	27.19	25.56	25.17

Table 3. Ablation Study for Frame Reconstruction in Office Lobby Dataset considering Single-View vs. Multi-View.

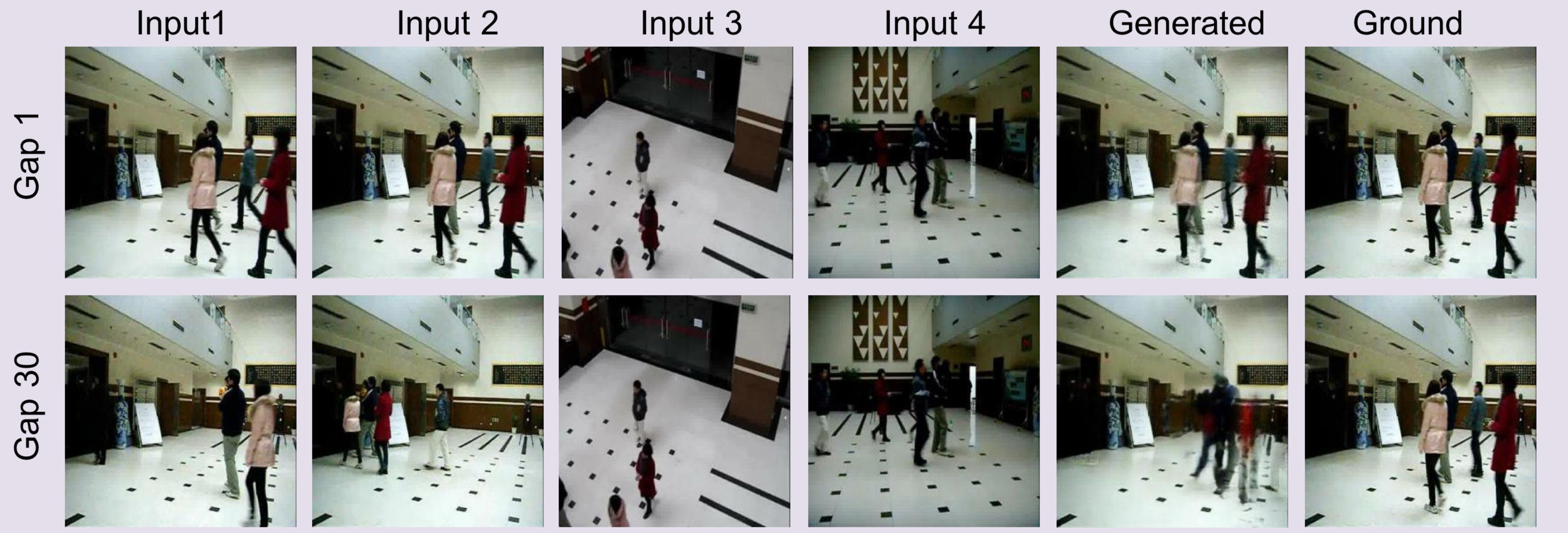


Fig 1. Two examples from Office Lobby Dataset where Input 1, Input 2, Input 3, and Input 4 are the preceding and the following frames of camera 1, and the corresponding frames of camera 2 and 3 respectively. As we increase the gap between the preceding and following frames with the missing frame, frames of camera 2 and camera 3 become more important. For example, due to the large number of missing frames in gap 30, the women in red dress is not visible yet in input 1 and her position is far away in input 2. Still, a person wearing a red dress is visible in the correct position of the generated frame incorporating information from the other two cameras.

7. Acknowledgements

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