Mind the Gap: Bridging Occlusion in Gait Recognition via Residual Gap Correction

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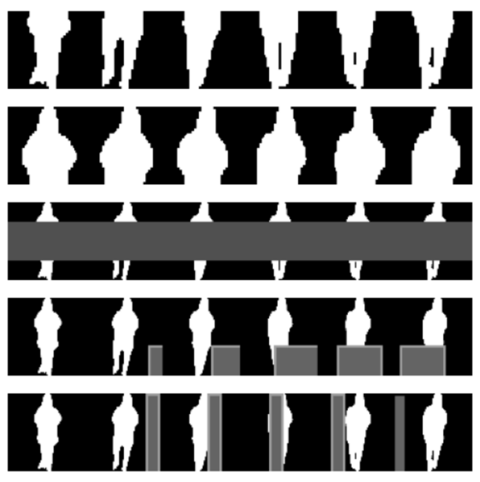
Introduction

We focus on the occlusion problem in gait recognition.

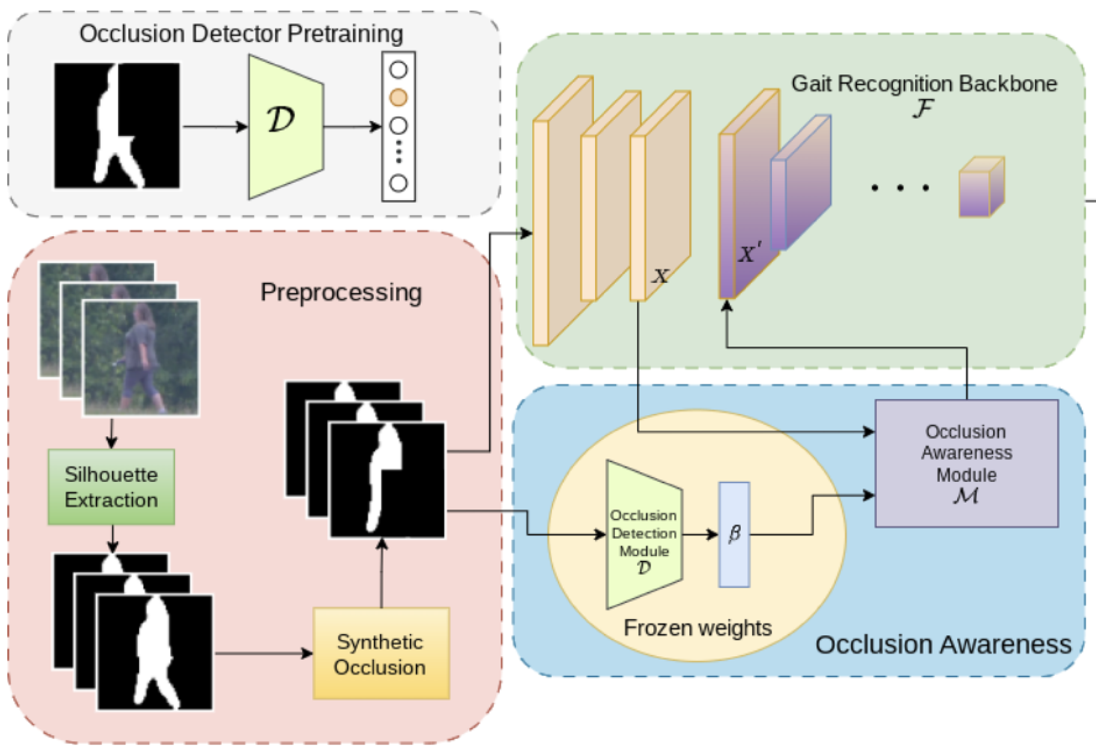


Existing works overfit to occlusions and can not perform well on holistic data and may need paired occlusion-holistic data for training.

We propose a training paradigm which

- **Does not require paired training data**
- Works for **both occluded and holistic data**
- Works with multiple backbone architectures, **model-agnostic**

Prerequisites

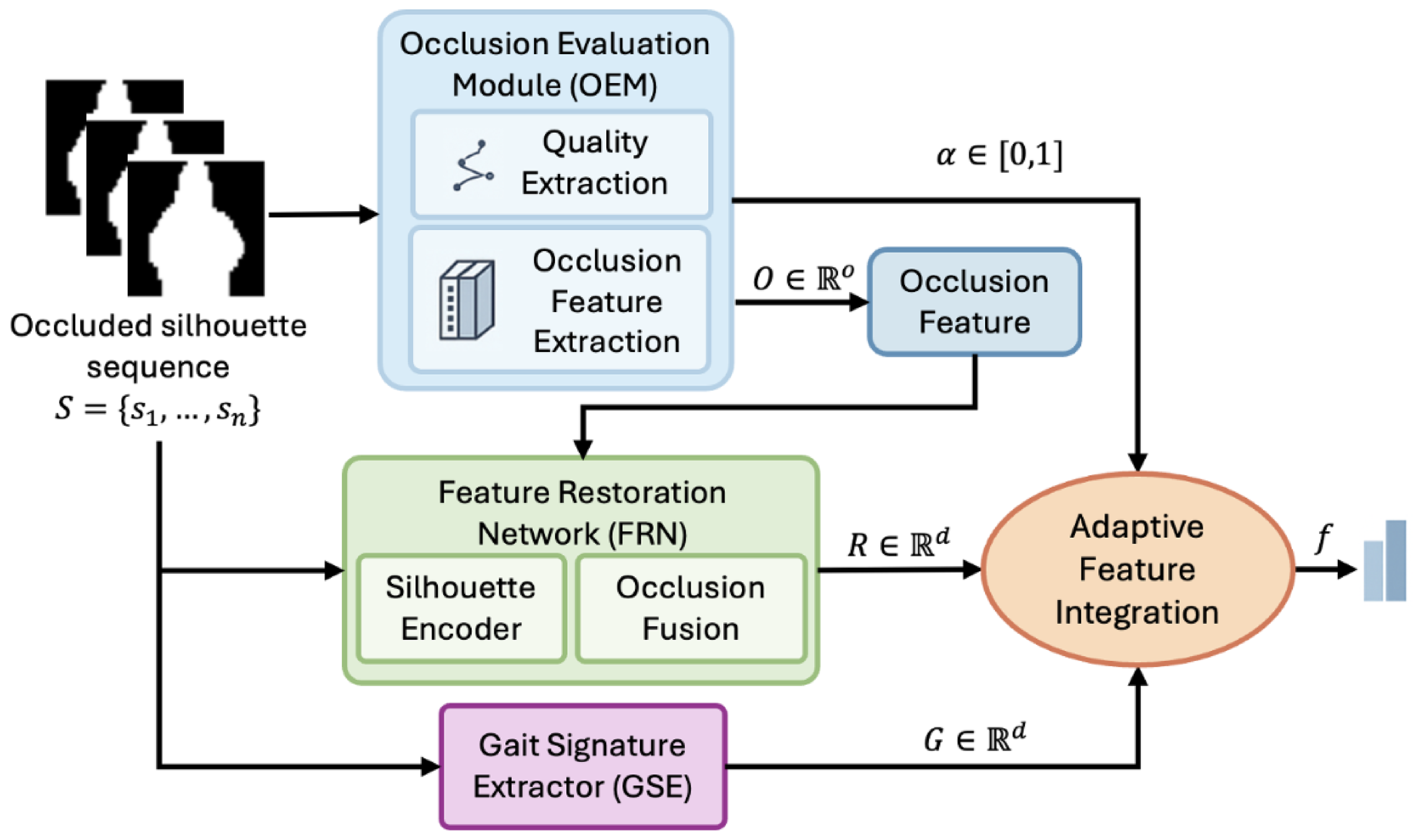


An **occlusion detector** can be used to **enhance a network's robustness to occlusion**, by implicitly making the network *occlusion aware*

Methodology: RG-Gait

Architecture

1. **Occlusion Awareness Module (OEM)** – External network for extracting occlusion features. Outputs occlusion features and a scalar residual weight **α** - strength of residual correction
2. **Gait Signature extractor (GSE)** – Base network, works well on holistic data
3. **Feature Restoration Network (FRN)** – Outputs a residual correction feature to correct GSE features under occlusions. Uses GSE outputs to become occlusion aware

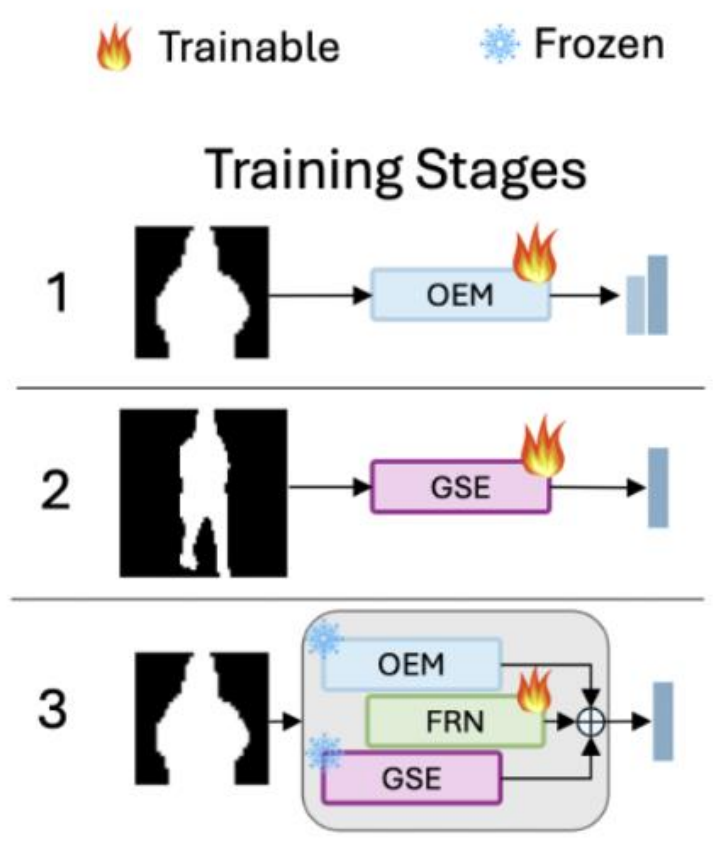


Methodology: Multi-stage training

Three stages – one module trained in every stage

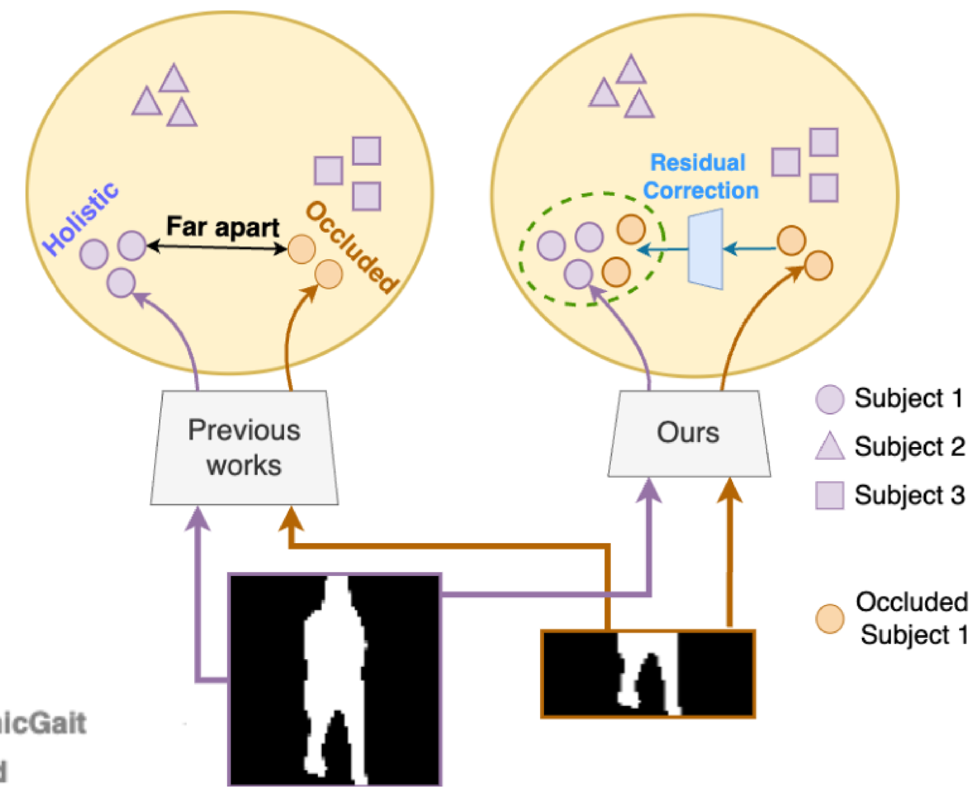
1. **Occlusion Awareness Module (OEM)** – Train OEM to recognize occlusions
2. **Gait Signature extractor (GSE)** – Train GSE to work on holistic data
3. **Feature Restoration Network (FRN)** – Train FRN to predict the residual deviations on GSE features

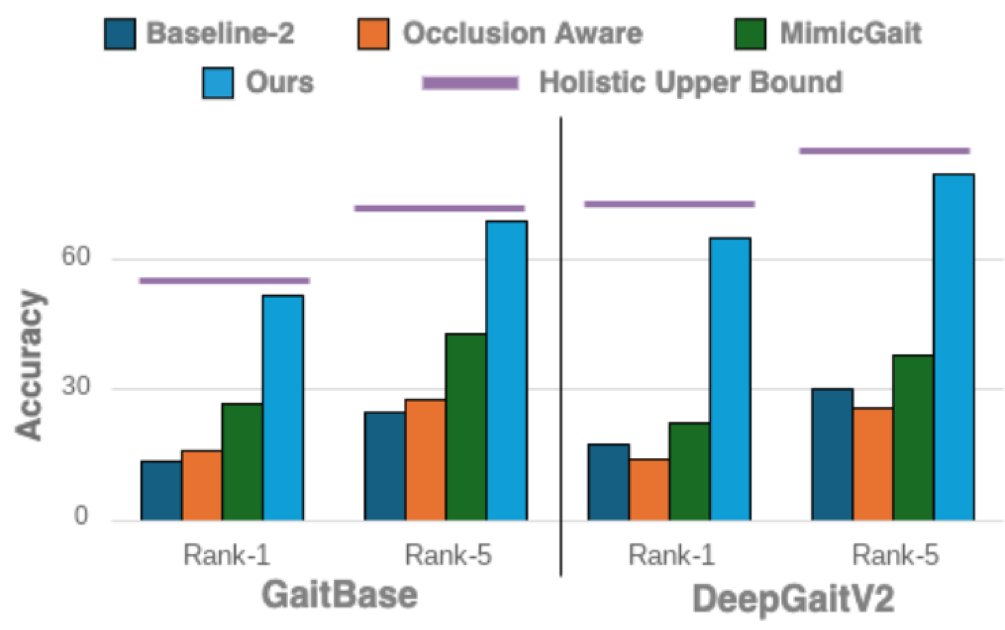
OEM guides the FRN to output correction features conditioned on the occlusion type and position!



Holistic Retention Problem

We identify a problem in existing approaches – **they work well on occluded data** but often **lose performance on holistic inputs**

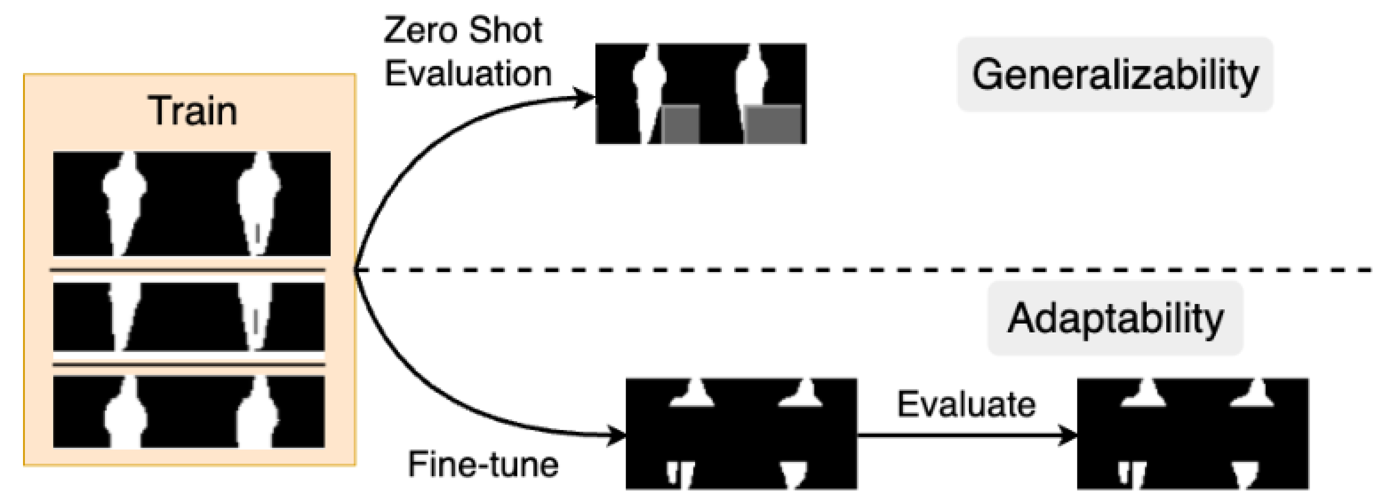




This resembles the classic problem of source forgetting in domain adaptation.

Training on occlusions (target) loses performance on holistic data (source)

Ablations and Analysis



Our method can **adapt** to new occlusions more easily and is **generalizable** to occlusions unseen during training.

Evaluation Type	Method	Middle Rank-1	Middle Rank-5	Dynamic Rank-1	Dynamic Rank-5
Generalizability	Occ Aware [8]	17.93	32.15	21.27	36.5
	MimicGait [9]	21.73	37.37	26.77	42.9
	RG-Gait (ours)	**37.7**	**55.25**	**39.12**	**55.45**
Adaptability	Occ Aware [8]	26.7	43.82	34.87	52.07
	MimicGait [9]	34.78	52.75	36.65	53.15
	RG-Gait (ours)	**47.62**	**63.57**	**48.72**	**64.92**

Ablation on residual learning:

All the components proposed in our **occlusion-aware residual integration framework** contribute to performance

Method	Residual learning	Adaptive Integration	Occlusion Awareness	Rank-1	Rank-5
Baseline-1	✗	✗	✗	7.6	15.71
Vanilla residual	✓	✗	✗	35.3	50.8
Aware only	✓	✗	✓	38.03	54.95
Adaptive only	✓	✓	✗	38.23	52.75
RG-Gait (ours)	✓	✓	✓	**40.84**	**57.25**

Acknowledgement

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