

Impact of Visual Data Anonymisation on Vision-Based Indoor Positioning

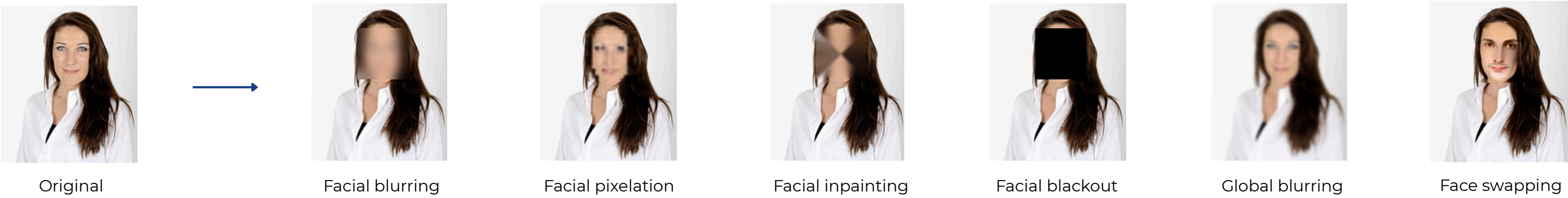
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Vision-based indoor positioning relies on rich visual information, yet people unintentionally captured by the system raise important privacy concerns. This work evaluates how different anonymisation strategies affect positioning performance and the preservation of scene information.

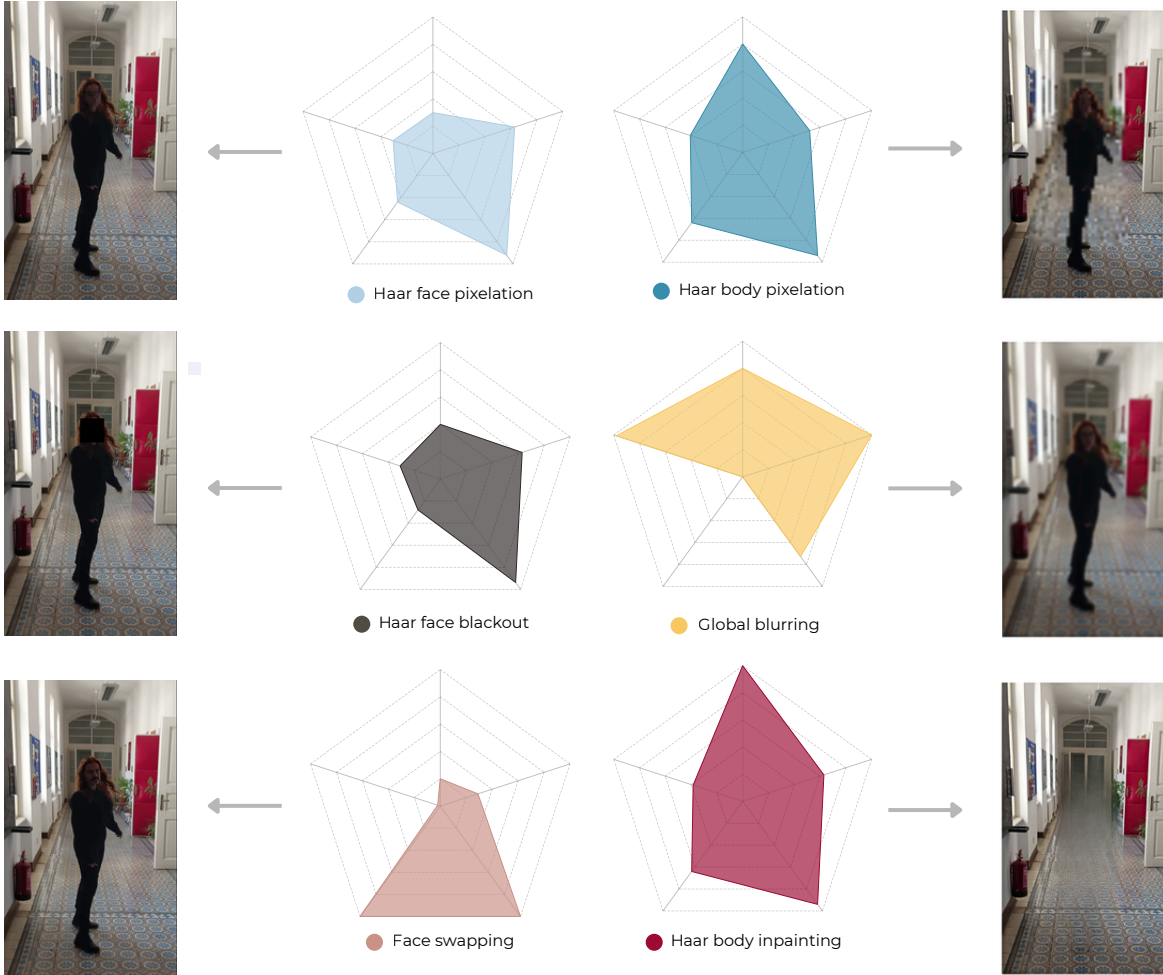
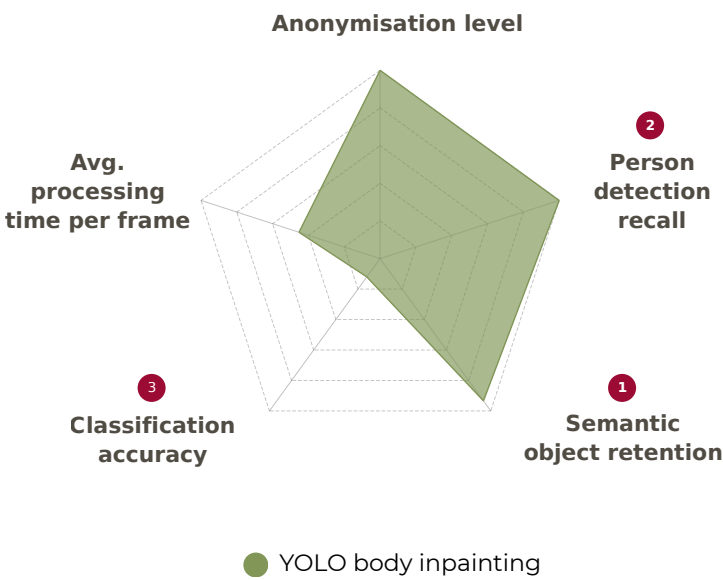
Privacy-Preserving Pipeline Evaluation

Which anonymisation strategy provides the best balance between privacy and positioning performance?

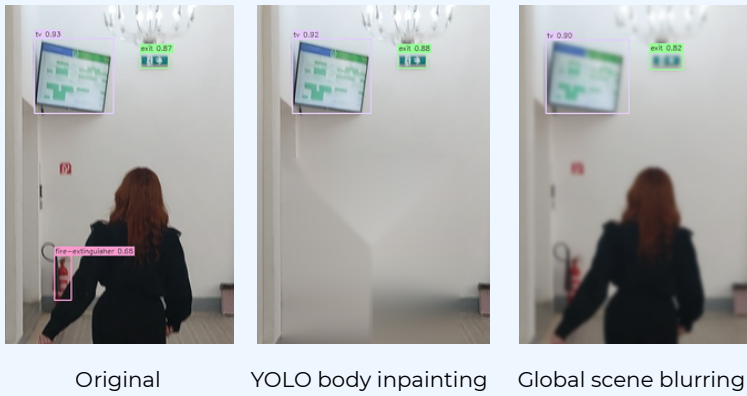


Multi-Criteria Comparison

No single metric is sufficient to evaluate anonymisation strategies - each represents a different trade-off across the evaluated criteria. Although positioning accuracy remained largely unaffected, several anonymisation strategies failed to anonymise all individuals due to limited person detection performance.



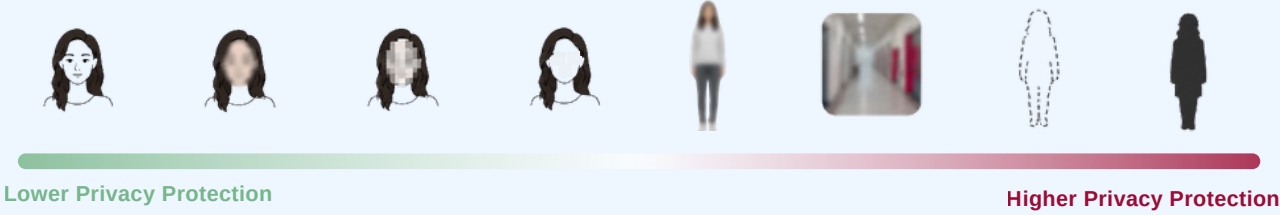
1 Impact on Semantic Object Retention



Scene-level anonymisation removes nearby semantic objects, whereas **person-centric anonymisation preserves most positioning landmarks**.

Sufficient anonymisation should protect primarily people rather than the entire scene, preserving semantic information required for reliable indoor positioning.

How much anonymisation is necessary?



The appropriate anonymisation level depends on the required privacy level and deployment scenario. From face masking to full-body removal, each strategy represents a different balance between privacy protection and scene preservation.

Face → Upper body → Full body → Global scene

Face swap minimally alters the surrounding scene, whereas body blackout provides stronger privacy protection at the cost of greater scene modification.

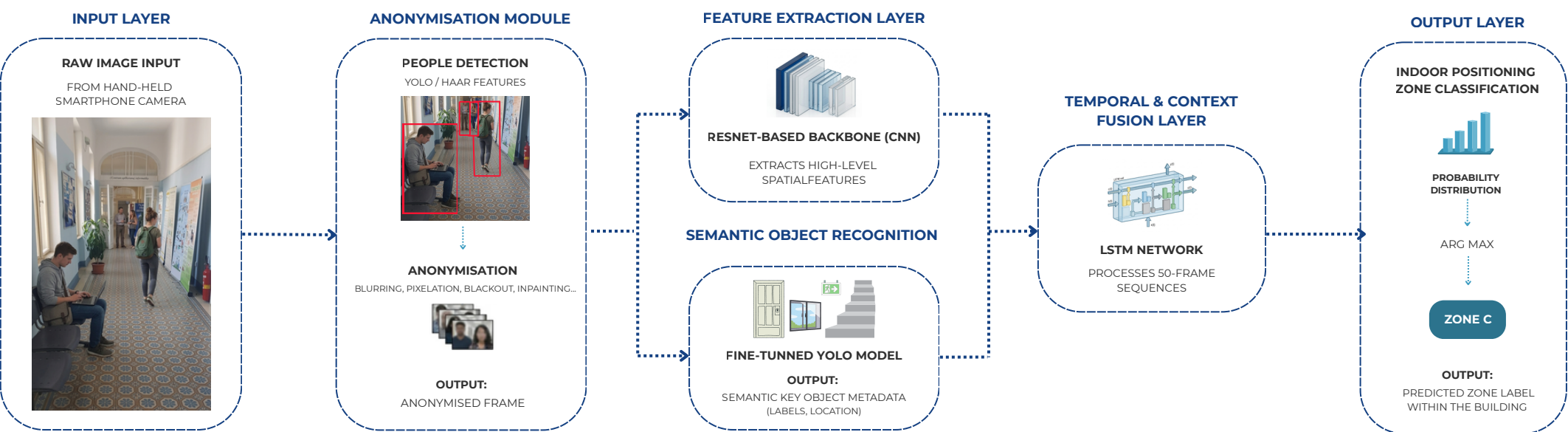
2 How reliably are people detected?

Detector	Recall
dlib (Shape Predictor 68)	29%
Haar cascade face	63%
Haar cascade body	52%
YOLO	98%

Evaluation performed on a representative subset of the collected dataset and independently validated on MOT15 benchmark.

How does anonymisation influence indoor zone classification?

The evaluated framework combines global visual features with semantic object recognition for indoor zone classification. Spatial and temporal information are fused to improve robustness in visually repetitive environments.



3 Anonymisation Impact on Positioning Performance

Anonym. Technique	Detection Method	Precision	F1	Accuracy	Semantic Obj. Retention
(none)	(none)	95.38%	95.08%	95.26%	100%
Blackout	Haar (face)	92.91%	92.02%	92.53%	93.79%
Blur	Haar (face)	92.42%	91.93%	92.01%	90.14%
Pixelation	Haar (face)	93.86%	93.12%	93.27%	91.73%
Pixelation	Haar (body)	94.24%	93.64%	93.82%	92.41%
Inpainting	Haar (face)	93.17%	92.41%	92.73%	92.35%
Face swap	SP68	95.35%	95.19%	94.65%	98.77%
Inpainting	YOLO	93.10%	92.55%	92.53%	93.40%
Global blur	(none)	92.78%	92.26%	90.89%	72.66%

Among the evaluated methods, face swapping provides the strongest balance between scene preservation and zone-classification performance.