

# **Dynamic Distance-based Shape Features** for Gait Recognition

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### **Gait Recognition**

- recognising a person via walking manner and posture
- medical and psychophysics fields show gait is unique
- fundamental healthy walking pattern is similar across persons but subtle variations in magnitude and timing aid person discrimination
- applications include surveillance and access control
- gait is a behavioural biometric (compared to physical e.g. fingerprint)
- no consent or cooperation, unobtrusive, capture at low resolution, distance

#### Motivation

- covariate factors decrease performance
- clothing, shoes, bags
- time between capture
- occlusion, viewpoint
- injury, drunkenness etc.
- causing pixel
- addition e.g. clothing adds bulk
- occlusion e.g. rucksack occludes arms
- shifting e.g. leaning due to bag carrying



Time +

Bag

Time +

Shoes

## Rough Skeletons

- classical medial axis sensitive to boundary perturbations
- smoothed distance function yields more robust skeletons
- $3 \times 3$  Sobel kernels convolved with smoothed distance function is superior
- screened Poisson skeleton thickness varies with smoothness parameter t





- robustness is imperative
- validation: TUM GAID database largest (155 persons) and latest
- training: 4 sequences (Normal)
- test: 2 sequences (Bag, Shoes, Time)

### Skeleton Variance Image (SVIM)

- pre-skeletonisation
- size normalisation
- horizontal alignment
- post-skeletonisation
- time normalisation
- pixel-wise variance
- single 2D image
- dimensionality reduction
  - representation = descriptor PCA + LDA maximises variance and class separability
- classification

Time +

Normal

Nearest Neighbour cosine distance

## **Smoothed Poisson-based Distance Functions**

- Poisson, normalized Poisson
- screened Poisson
- pros: tunable smoothness
  - parameter t
- cons: higher computational cost



#### low boundary perturbation sensitivity (imperfect silhouette segmentation)

compared to true Euclidean distance function

normalized Poisson

	Descriptor	N	В	S	TN	ΤB	TS	Avg <sub>w</sub>
		(%)	(%)	(%)	(%)	(%)	(%)	(%)
Appearance	GEI	99.7	19.0	96.5	34.4	0.0	43.8	67.5
	DGHEI	99.0	40.3	96.1	50.0	0.0	44.0	74.1
	SEIM t=0.5	96.1	8.7	84.8	21.9	0.0	18.8	58.6
	SEIM t=5	98.4	14.8	88.7	28.1	0.0	34.4	63.0
	SEIM t=50	99.0	17.7	93.9	28.1	0.0	28.1	65.4
	SEIM poisson	97.4	8.1	89.7	40.6	3.1	28.1	61.2
	SEIM norm. poisson	99.0	18.4	96.1	15.6	3.1	28.1	66.0
Motion	GVI	99.0	47.7	94.5	62.5	15.6	62.5	77.3
	SVIM t=0.5	98.1	63.9	86.8	62.5	34.4	50.0	79.7
	SVIM t=5	98.4	64.2	91.6	65.6	31.3	50.0	81.4
	SVIM t=50	97.7	51.9	93.9	59.4	37.5	53.1	78.3
	SVIM poisson	97.4	53.6	88.1	65.6	21.9	53.1	76.6
	SVIM norm. poisson	98.4	54.2	92.9	50.0	28.1	37.5	77.8

#### Discussion



Poisson

covariate factors significantly affect appearance shoes e.g. heels or flip flops may decrease performance further SVIM more robust across the majority of covariate factors emphasis on body motion compared to covariate factors performance 10% better than existing state of the art screened Poisson distance function more robust tunable smoothness parameter t (may be application dependent) small t values risk skeleton segmentation at branch points large t values cause thick skeletons like silhouettes

#### Conclusion

- efficient skeleton extraction via screened Poisson equation includes tuning smoothness parameter t
- powerful and robust gait descriptor Skeleton Variance Image gait motion more consistent over time than appearance