COMBINING IMAGES AND WORDS IN DEEP NETWORKS THAT IDENTIFY PEOPLE FROM BODY SHAPE

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OVERVIEW

- Problem person identification based on body shape
 - Biometric Recognition and Identification at Altitude and Range (BRIAR)
 - IARPA <u>https://www.iarpa.gov/research-programs/briar</u>
- Linguistic descriptors to "quantify" body shape
 - psychology, computer graphics
- Body identification networks:
 - linguistic descriptors
 - object-based shape descriptors
- Person recognition = face + body + gait
 - fusion

PROBLEM



face body gait

subjects consented to publication







controlled close range



UAV



subject consented to publication

same person or different people?



face



gait



subjects consented to publication

BODY AS A BIOMETRIC

- Why use body?
 - visible at large distances
 - subset of cues constant over change in view
 - height, weight, proportions, rough shape
 - "fusability"
 - You have no other option!

BODY IS LEAST COMMON DENOMINATOR



subjects consented to publication

BODY AS A BIOMETRIC

- Why not use body?
 - not unique
 - lack of a body algorithms
 - •face
 - gait
 - body





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LINGUISTIC DESCRIPTIONS & 3D BODY SHAPES

Hill, Matthew Q., et al. "Creating body shapes from verbal descriptions by linking similarity spaces." *Psychological science* 27.11 (2016): 1486-1497.

Streuber, Stephan, et al. "Body talk: Crowdshaping realistic 3D avatars with words." *ACM Transactions on Graphics (TOG)* 35.4 (2016): 1-14.

HUMAN BODY SHAPE



- body = complex 3D shape
 - Laser scan = 12500 vertices and 25000 facets

LINGUISTIC DESCRIPTIONS OF BODIES

- muscular, athletic
- stout, portly
- shapely, hourglass



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RATIONALE

- human language and vision
 - evolved a long time ago
 - 50K and 2 million years ago
 - words don't leave fossils or tool fragments
 - language communicates information efficiently
 - not every vertex in the laser scan carries a lot of information

long legs lean curvy

APPROACH

- human descriptions to create a similarity space
 - point proximity -> similarity between **body descriptions**
- geometric shape space to ground-truth description space
 - point proximity -> similarity between **body shapes**



BODY DESCRIPTIONS



	Construction of the second sec
Proportioned	\odot \bigcirc \bigcirc
Rectangular	\odot \bigcirc \bigcirc
Stocky	\odot \bigcirc \bigcirc
Short legs	\odot \bigcirc \bigcirc
Muscular	\odot \bigcirc \bigcirc
Average	\odot \bigcirc \bigcirc
Tall	\odot \bigcirc \bigcirc
Sturdy	\odot \bigcirc \bigcirc
Big	\odot \bigcirc \bigcirc
Long legs	\odot \bigcirc \bigcirc
Lean	$\odot \circ \circ$
Short torso	\odot \bigcirc \bigcirc
Pear shaped	$\odot \bigcirc \bigcirc$
Petite	\odot \bigcirc \bigcirc
Broad shoulders	\odot \bigcirc \bigcirc
Heavyset	\odot \bigcirc \bigcirc
Long	\odot \bigcirc \bigcirc
Long torso	\odot \bigcirc \bigcirc
Round (Apple)	\odot \bigcirc \bigcirc
Built	\odot \bigcirc \bigcirc
Fit	\odot \bigcirc \bigcirc
Skinny	\odot \bigcirc \bigcirc
Masculine	\odot \bigcirc \bigcirc
Small	\odot \bigcirc \bigcirc
Short	\odot \bigcirc \bigcirc
Feminine	\odot \bigcirc \bigcirc
Curvy	\odot \bigcirc \bigcirc



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Descriptor Terms								
proportioned	sturdy	broad shoulders	skinny					
rectangular	big	heavyset	masculine					
stocky	long legs	long	small					
short legs	lean	long torso	short					
muscular	short torso	round (apple)	feminine					
average	pear shaped	built	curvy					
tall	petite	fit						

LANGUAGE SPACE DATA

- Body representations:
 - descriptions made from <u>images</u> of people

LANGUAGE SIMILARITY SPACE

• applied **correspondence analysis** to:

- descriptor vectors for the 164 female bodies
 - 27 elements terms that "applied perfectly" to the body
- Correspondence Analysis (CA) (Benzicri, 1973)
 - multivariate analysis analogous to PCA, but for categorical data
 - allows observations (bodies) to be plotted in the same space as the variables (descriptor terms)

LANGUAGE SPACE

(IST & 2ND AXES)



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LANGUAGE SPACE (3ST & 4TH AXES)



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GROUND TRUTH LINGUISTIC DESCRIPTION SPACE WITH 3D BODY MODEL SPACE



Body model PCA of laser scans of bodies (Loper et al., 2016)

3D BODY SYNTHESIS FROM DESCRIPTIONS



PCA of 3000+ laser scans SMPL model (Loper et al., 2016)

subjects consented to publication









subject consented to publication

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Streuber et al. (2016)



CONCLUSIONS

- linguistic descriptions
 - can be used to synthesize 3D bodies

 efficient way to perform a laser scan without a laser scanner ^(C)

IDENTIFICATION FROM BODY SHAPE

Myers BA, Jaggernauth L, Metz TM, Hill MQ, Gandi VN, Castillo CD, O'Toole AJ. Recognizing People by Body Shape Using Deep Networks of Images and Words. arXiv:2305.19160. 2023 May 30. *Proc. IEEE International Joint Conference on Biometric, Sept. 2023*

WORDS FOR BODY IDENTIFICATION

Rationale

-descriptors sufficient to synthesize 3D body

- descriptor-based representation for identification?
- Advantages
 - robust across large distances
 - generalize across yaw and pitch (curvy, tall, stout, long legs,)
 - accessible across a range of view
 - (relatively) clothing independent
 - Explainable Al??

CURRENT PROBLEM

- learn mapping from images to descriptors
 - pretraining to categorize body shape
- image to identity
 - transfer learning image to identity
 - fine tuning within a category



MODELS

• linguistic body model (LCRIM)

- linguistic core model
 - body image to linguistic description
- identity-tuning
 - body image to identity
- non-linguistic body model (NLCRIM)
 - pre-trained object classification core model
 - ImageNet trained
 - identity-tuning
 - body image to identity
- Fusion = LCRIM + NLCRIM







UAV





100m

200m 40



500m

training

 577 IDs
 242,386 images

• test

- 485 gallery IDs
 - 43,722 images
- 260 probe IDs

• 2,192,305 image frames from 9,795 videos

(BRS-BTS dataset, Cornett, et. al., 2022)



Cumulative Match Characteristic



Receiver Operating Characteristic Curve



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DISTANCE CONDITIONS

• Linguistic > as views and pitch get more extreme?









LCRIM > NLCRIM

FUSION >> (NLCRIM OR LCRIM)



LINGUISTIC? NON-LINGUISTIC? FUSED?

- condition-dependent
 - fusion *almost* always best

- linguistic/non-linguistic
 - less predictable

CONCLUSIONS

- Linguistic descriptors
 - complement body shape representations
 - better at further distances (tentatively)
 - tap similar types of information

PERSON = FACE + BODY + GAIT

FUSION, VARIANCE, QUALITY



LIMITS OF THE BODY

same person or different people?

same person or different people?

same person or different people?

FACE, BODY, & GAIT: MODEL (DIS)AGREEMENT

		Body 1	Body 2	Body 3	Face 1	Face 2	Gait	
	_							
		0	1	2	3	4	5	
Body 1	0	1	0.44643	0.446626	0.186319	0.185375	0.15463	
Body 2	1	0.44643	1	0.785518	0.25484	0.255659	0.346526	
Body 3	2	0.446626	0.785518	1	0.250673	0.251236	0.352391	
Face 1	3	0.186319	0.25484	0.250673	1	0.660499	0.127177	
Face 2	4	0.185375	0.255659	0.251236	0.660499	1	0.132766	
Gait	5	0.15463	0.346526	0.352391	0.127177	0.132766	1	



Fusion

Face Fusion

Body Fusion





Yovel & O'Toole (2016)

APPROACH

- fusion on a case-by-case basis
 - requires **quality** of face vs. body vs. gait with limited meta-data
- What happens when they do not agree?
 - face with body?
 - face with face? body with body?
 - gait with face or body?

• Can disagreement be informative of quality???

VARIANCE OF ESTIMATES

- Proposal
 - Can variance of model estimates guide fusion?

- Predict
 - high variance indicates "low quality" and low accuracy
- Prerequisite (sanity test)
 - Does variance of model estimates relate to accuracy?

DOES MODEL VARIANCE PREDICT ACCURACY?

• Variance on each item

- all-model variance
- face-model variance
- body-model variance
- Performance:
 - face fusion similarity scores (2 face algorithms)
 - body fusion similarity scores (3 body algorithms)



Low variability model scores - better performance with body information



Low variability body models better performance with body



Low variability face models better performance with body



Low variability face models better performance with the face

2 INVERSIONS



High variability model scores **better** performance with the face (except at very low FP)



High variability body estimates better performance with face!

TAKE HOME MESSAGE

- Biometrics has ignored the body on the (correct) premise that it is not "unique"
 - not unique **‡** not helpful
- Linguistic descriptions of bodies
 - graphics, shape classification, identification
- Body algorithms boost identification over
 - face
 - gait
- Quality estimates from model discord within/across modalities

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