

Gait recognition via deep learning of the center-of-pressure trajectory: A proof-of-concept study for biometric applications

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Background

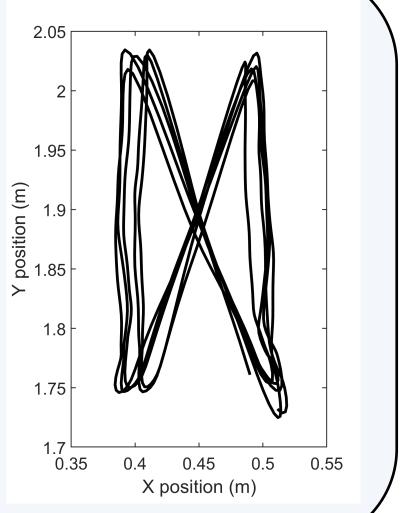
- Biometrics refers to verifying or identifying a person according to his/her biological or behavioral characteristics
- Gait is the coordinated, cyclic combination of movements that result in human locomotion.
- Gait recognition means authenticating a person by his/her manner of walking

Research gap

It is possible to record foot trace on the ground through pressure sensors embedded in the floor.

While walking, the center-of pressure trajectory has a typical butterfly-like shape [2]. The "wings" of the butterfly correspond to the stance on a single foot, while the central crossing corresponds to the double-support phase when the body weight passes from one foot to the other.

To date, no study harnessed this typical trace for identification purposes.



Objective

The objective was to bring a proofof-concept that measuring foot pressure on the floor can be employed for biometry purposes.

A deep convolutional network was used to extract the features of pressure trajectories and to classify the gaits of 36 individuals.

Instrument

- Instrumented treadmill (300 x 70 cm)
- Vertical force and pressure trajectory recorded at 50Hz
- Participants walked at preferred walking speed [1]
- Three conditions: no cueing, auditory cueing, visual cueing

	3 x ~10 minutes tread	nill walking	Data segmentation
Procedure and Condition #1 data Condition #1 processing Condition #2	Train Train	Dev Test Dev Test	
Condition #3	Train 3 x 500 strides (1 str	Dev Test ide = 2 steps)	
 The 500-strides time series we resampled to 20,000 samples samples per strides). The dataset contains three 2D 	ere (40 ******* 30 ****** mo	participants for del building and ting	ID #3 ID #4 ID #4
nals of 20,000 sample length f each of the 36 participants. To 54,000 strides (108,000 steps	tal = 'N'N'N'N'N'N s). Ann Ann 6 p	articipants for nsfer learning	2D signals were sliced into 80-s length segments (2 strides, or 4 labelled with participants' ID.

were sliced into 80-sample nents (2 strides, or 4 steps), n participants' ID.

Deep convolutional neural net-	
	Convolution
work (CNN)	Activation
	Convolution
	Activation
 The CNN is directly feeded with the 	Max. Pooling (2)
segments of dimension: [batch size x 8	0
	Convolutio
X ZJ	Activation

Hyperparmeter tuning and a	ccuracy results
Training set	Development set
18,000 segments	2,250 seg.

Tuned hyperparameters:

Transfer learning: method

- Most CNN parameters were frozen,
- Only the weights of the last two convolutional layers were further fine-tuned
- The output (softmax) layer was replaced

- 700,000 parameters
- 1D convolutional layers interleaved with Max Pooling layers
- Batch normalization
- Activation: sigmoid weighted linear unit (trainable Swish)
- Residual shortcuts (ResNet)
- Regularized via L2 weight decay
- Loss function: categorical crossentropy
- Mini-batch optimizer for gradient descent: Adam

Convolution Activation Convolution Activation Convolution Activation Convolution Max. Pooling (2) Activation Convolution Activation Max. Pooling (3) Convolution Global Avg. Pooling Dense (SoftMax)

Number of layers | Number of filters in layers | Filter size | Regularization strength | Activation algorithm | Initial learning rate

> Training + dev sets Test set 2,250 seg. 20,250 segments

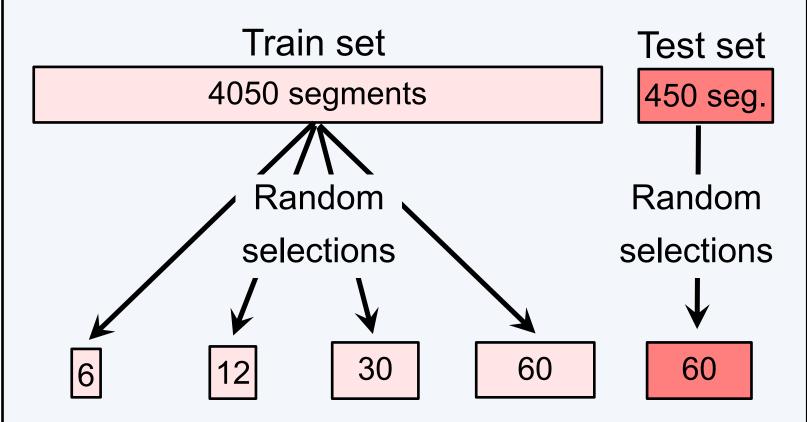
Overall classification accuracy on the test set:

10 repetitions of learning / assessment. Try to correctly classify the segments belonging to each of the 30 participants.

2,246 correct classifications

2,250 total number of examples

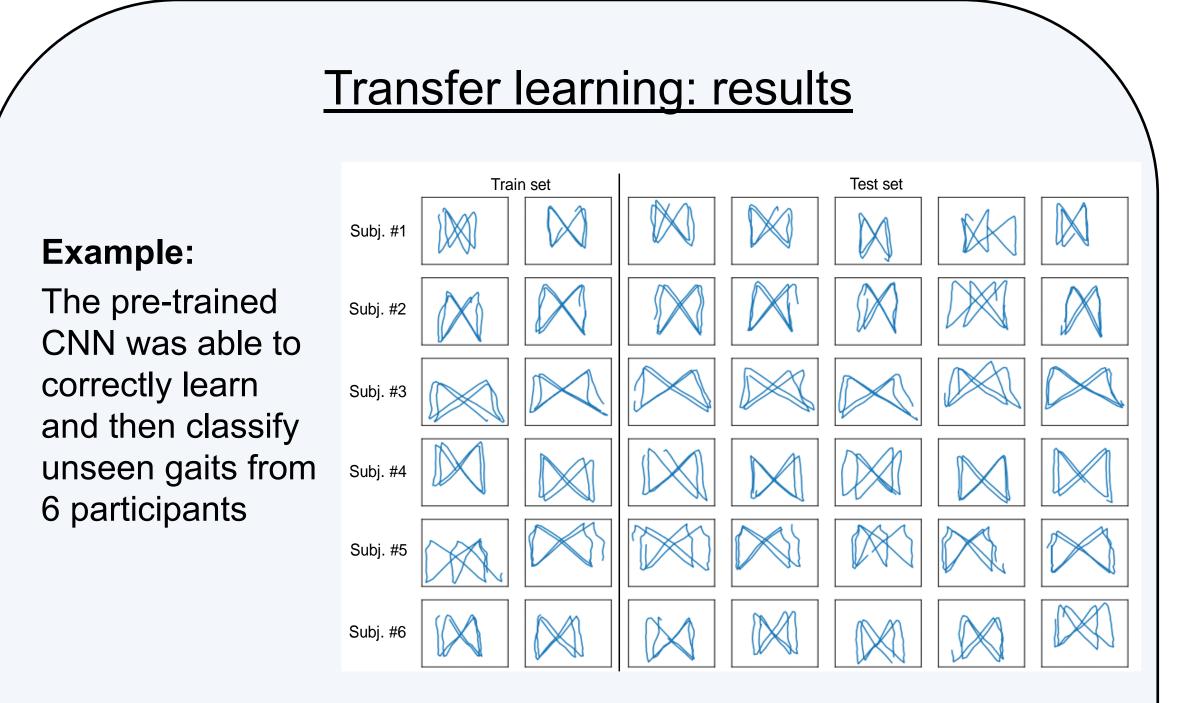
with a new layer with six neurons to match the new classification task.



4x50 repetitions with different number of segments in the training set, from 1 per subject, to 10 per subject

Take Home message

- The center-of-pressure trajectory of a walking person has a unique butterfly-like shape
- A deep CNN can learn from



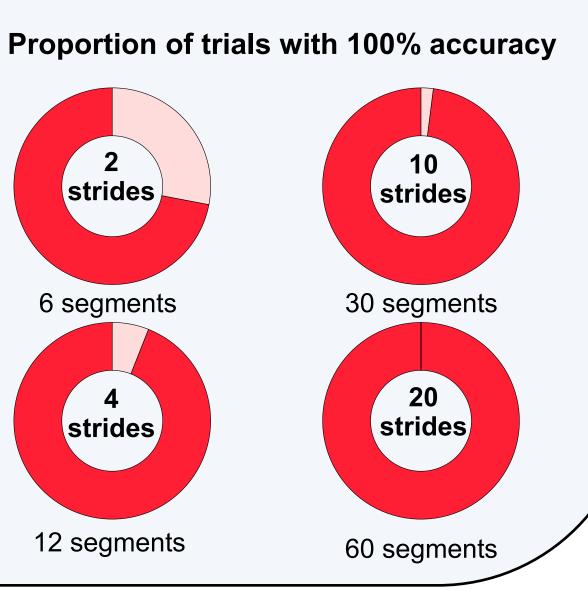
Discussion

-= 99.8%

Previous studies have demonstrated that floors sensitive to foot pressure of walking individuals can be used for identification purposes [3].

Butterfly-like traces corresponding to the centerof-pressure trajectory can be collected from pressure sensitive floors by subtracting the average speed vector from position data.

Over the 200 random trials, the pre-trained CNN was able to reach 100% accuracy in 182 trials. With only 1 segment (2 strides) per subject in the training set, the CNN was already able to reach 100% accuracy in 36 over 50 trials.



Here, I show that these traces are unique for each individual, and can be easily learned by a deep convolutional neural network.

Future studies are needed to extend the finding of the present laboratory study to less controlled environments.

In particular, the long term variability of foot pressures and the influence of footwear should be further investigated.

these unique shapes to recognize people with a high confidence

• A pre-trained CNN can further learn new gaits from previously unseen individuals by being trained with only 2-4 strides.

References

[1] P. Terrier, "Fractal Fluctuations in Human Walking: Comparison Between Auditory and Visually Guided Stepping," Ann Biomed Eng, vol. 44, n° 9, p. 2785–2793, 2016.

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logical and cerebellar impairment in people with multiple sclerosis," J. *Neurol. Sci.*, vol. 358, no. 1–2, pp. 92–100, Nov. 2015.

[3] J. Suutala and J. Röning, "Methods for person identification on a pressure-sensitive floor: Experiments with multiple classifiers and reject option," Information Fusion, vol. 9, no. 1, pp. 21–40, Jan. 2008.