Gait Sequence Modelling and Estimation using Hidden Markov Models

Kouame H. Kouassi
ksskou001@myuct.ac.za

Abstract

In the present work, gait sequence modelling and estimation was performed with Hidden Markov Models (HMMs) from inertial measurement unit (IMU) data. More specifically, from IMU measurements, a dog's footfalls were correctly identified with up to 95% precision. The continuous-valued IMU measurements were modelled with Gaussian mixtures.

Model Parameters

- $\pi = \{\pi_i\}$, the initial state distribution as prior knowledge
- $A = \{a_{ij}\}$, the state transition probabilities. a_{ij} denotes probability of transitioning from state S_i to state S_j.
- $\Phi = \{\phi_j(k)\}$, Gaussian distributions characterised by the mean matrix: μ_{jm}, the co-variance matrices Σ_{jm}, and the mixture distribution: β_{jm}.

Dimensionality reduction

Feature ranking with separability of index (SI): Features' are ordered according to their between-class **'classifiability content'** using mahalanobis distance
Forward feature selection: forward feature selection with a prior reduction using SI ranking
PCA: The four principal components (PC) were selected to represent the dataset in the PC-space.
LDA: The data was reduced to 3-dimensions using Linear Discriminant Analysis.

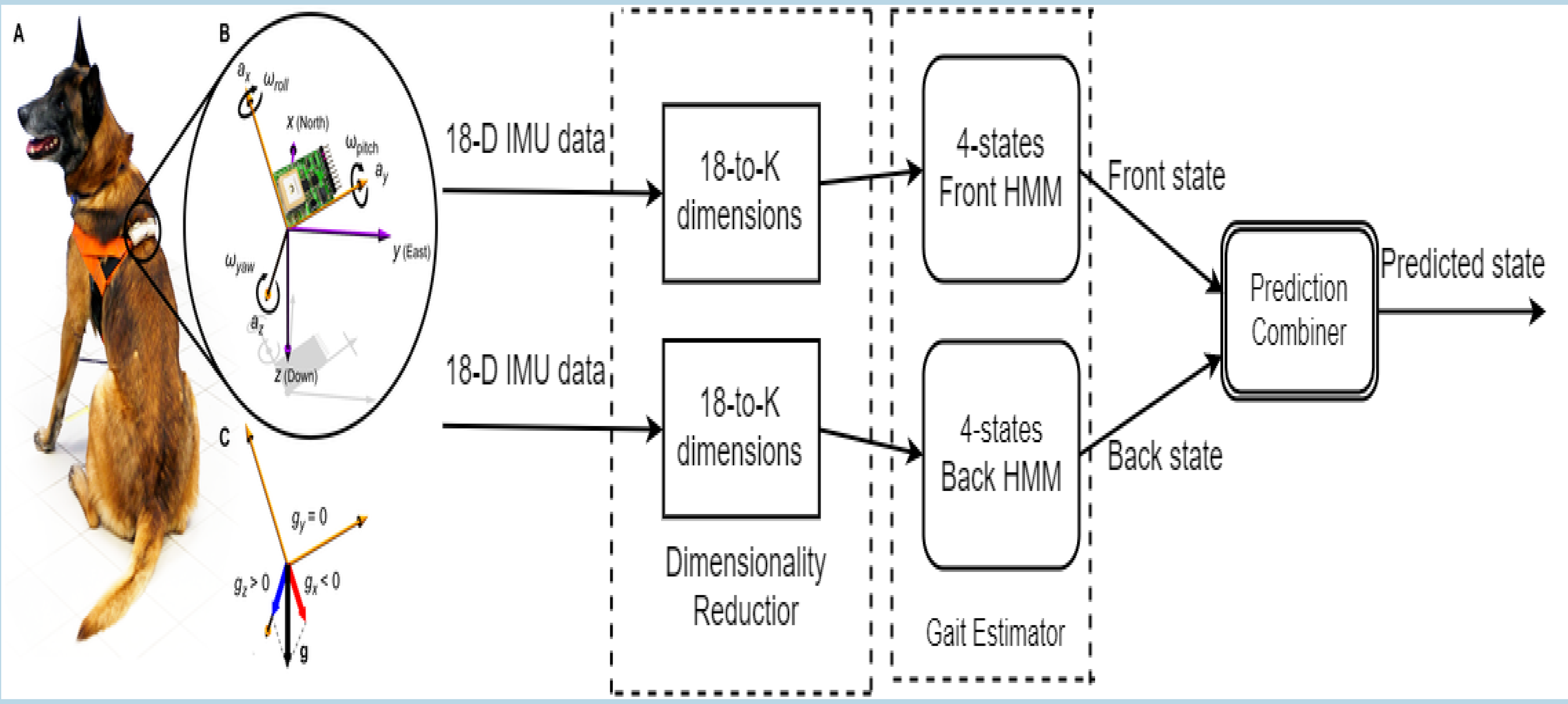
Parameter estimation

Increase the data by mirroring and aggregation: The reverse gait sequence was appended to the (aggregated) initial IMU measurement sequence.
Transition matrix, A: Using the available ground-truth, the HMM was reduced to a discrete Markov problem to estimate the transition probabilities.
Gaussian Mixture parameter, μ_{jm}, Σ_{jm}, and β_{jm}: The parameters were initialised with *kmeans++*, then optimised with the *Expectation-Maximisation* algorithm with the training samples.
Initial state distribution (*Snapshot preferential*) G_0 is a scale free network. Add k_A edges from a random node with preferential attachment based on the snapshot network. Delete k_D existing edges.

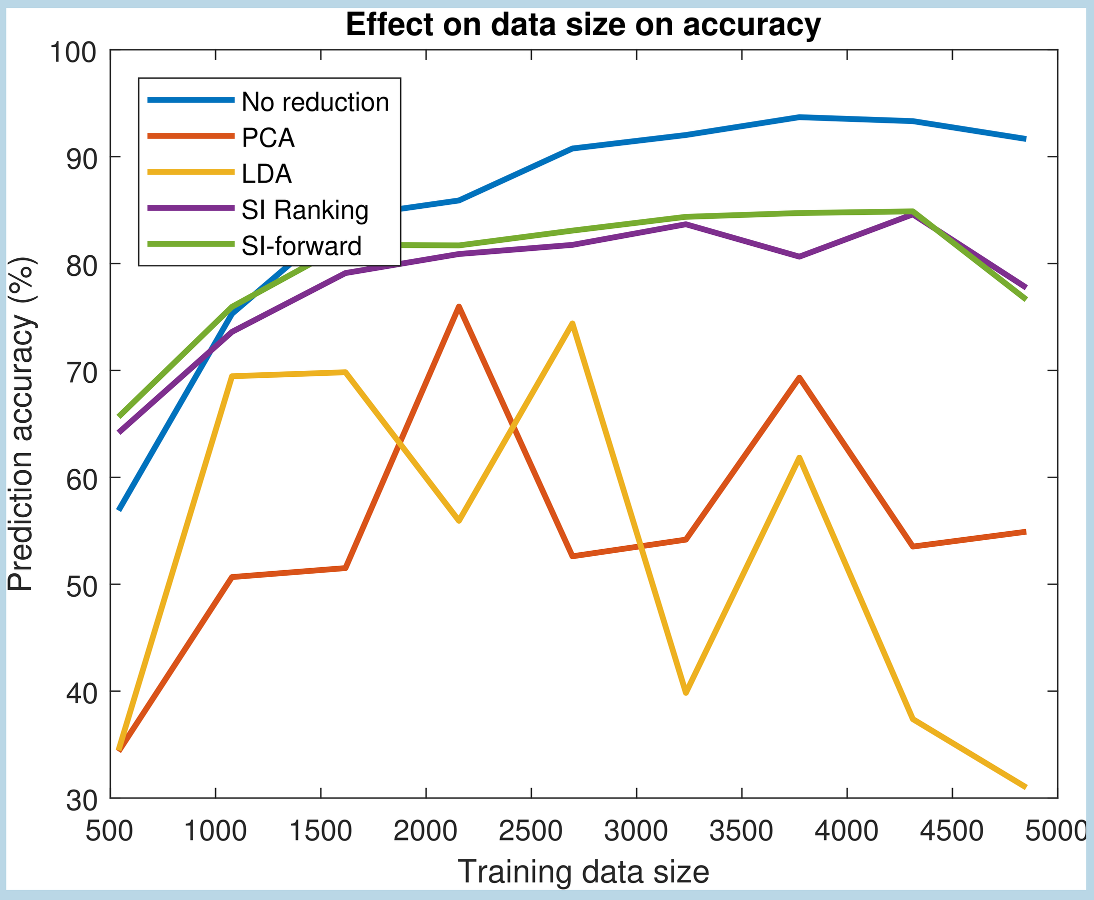
Footfall Prediction

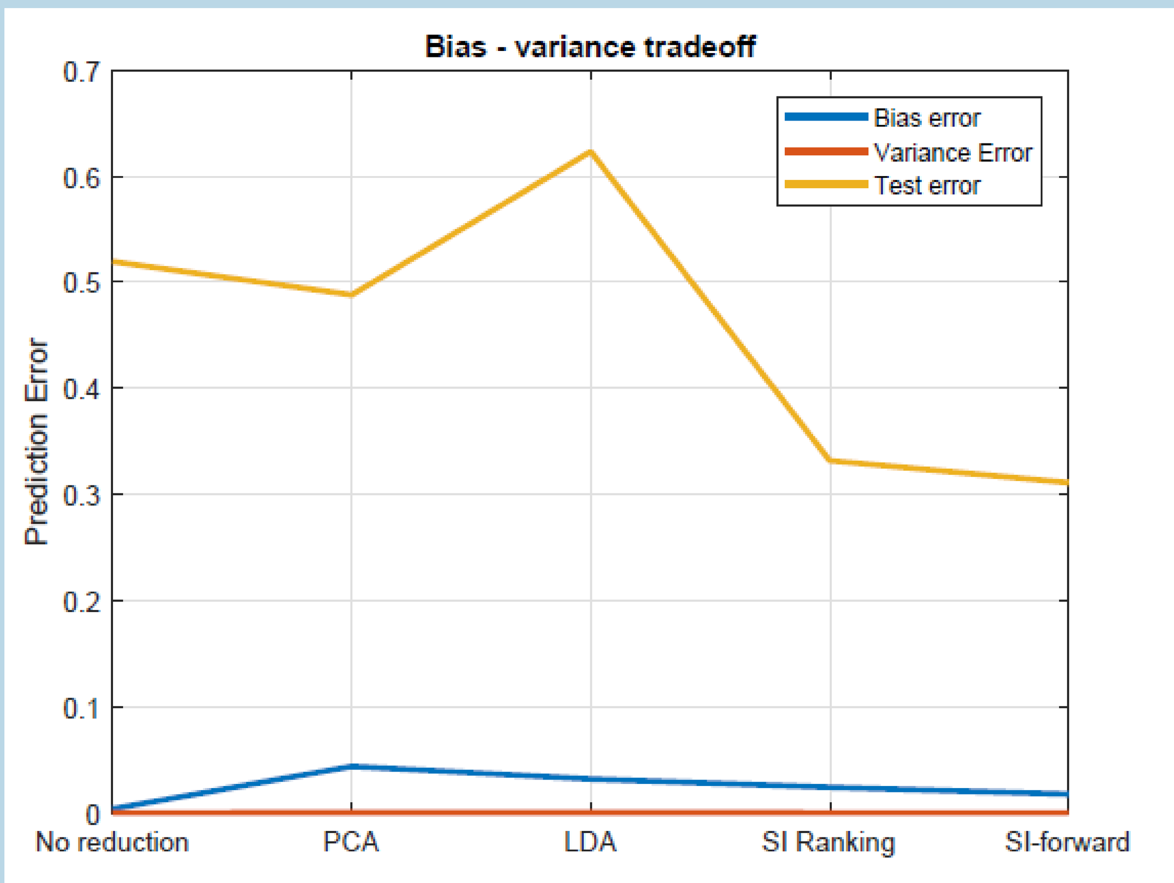
Given a sequence of observation, the dog's successive positions (the hidden states) are determined using the
pi, A, and Φ. Practically, the **Viterbi algorithm** was used to predict the hidden state sequence.

Gait Estimation System Overview

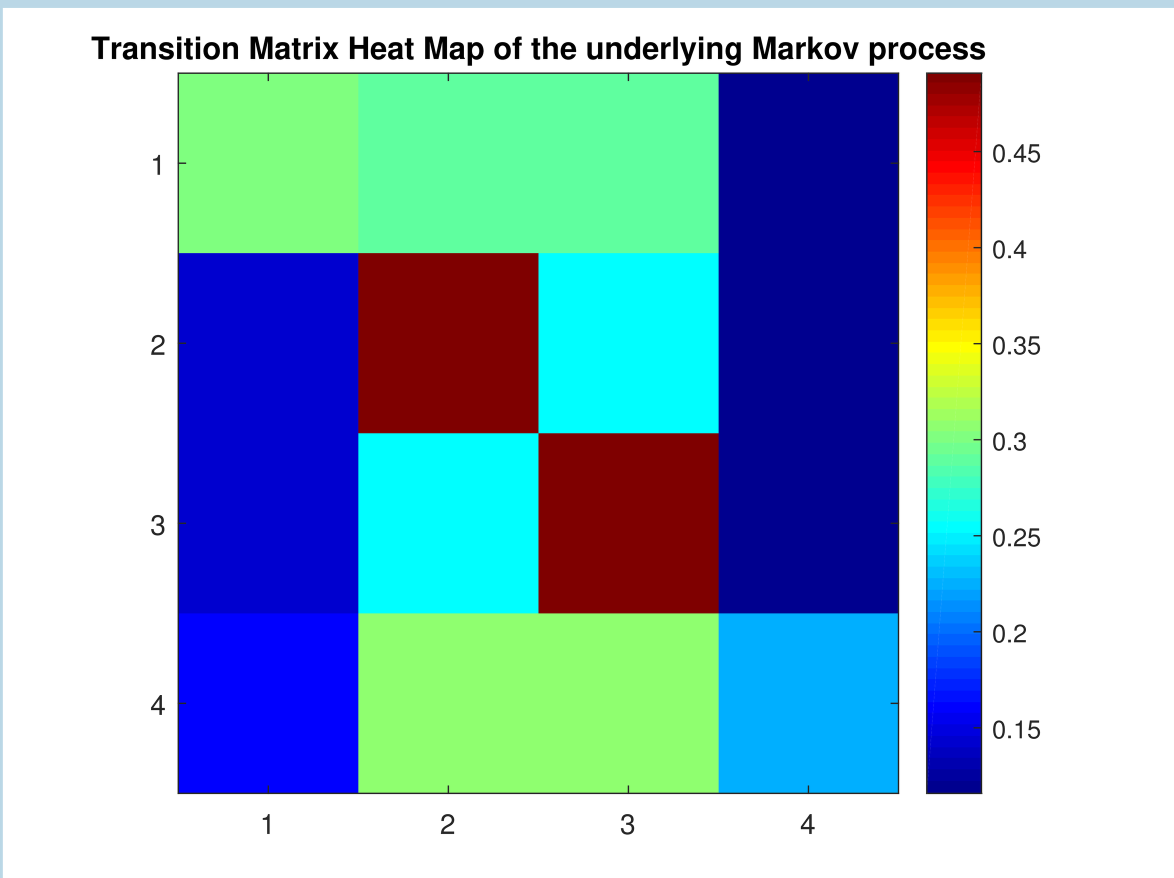


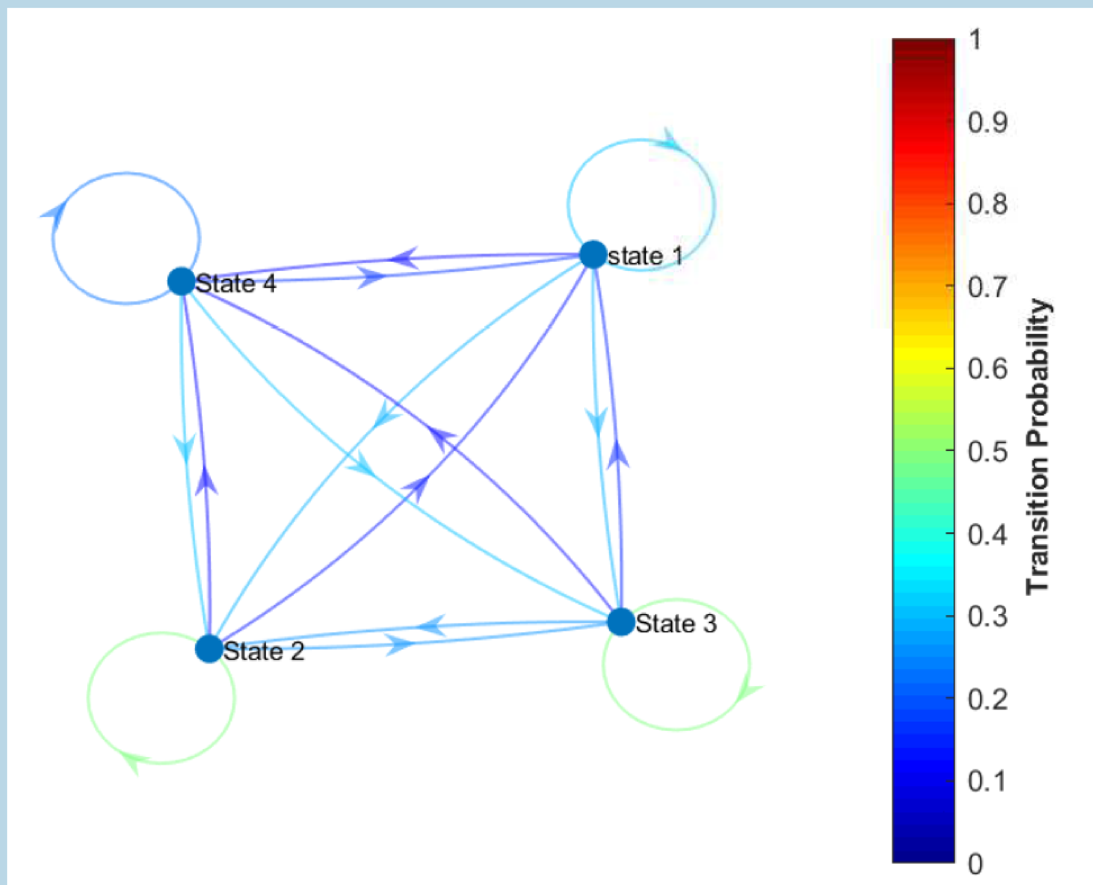
Effect of Dimensionality Reduction





State Transition Markov Process





Motion Type Recognition

	Running Data	Walking Data	Trotting Data
Model of Dog's Run	91.16%	2.06%	0.22%
Model of Dog's Walk	21.06%	100.00%	75.53%
Model of Dog's Trot	27.40%	45.72%	100.00%

Table 1: Dog's motion type recognition with prediction accuracy

	Running Data	Walking Data	Trotting Data
Model of Dog's Run	0.00	-0.00×10^{14}	-0.00×10^{14}
Model of Dog's Walk	-0.00×10^{14}	0.00	-0.00×10^{14}
Model of Dog's Trot	-1.44×10^{12}	-0.1302	0.00

Table 2: Dog's motion type recognition with sequence's log-likelihood