

METHODS & TECHNIQUES

An exploratory clustering approach for extracting stride parameters from tracking collars on free-ranging wild animals

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ABSTRACT

Changes in stride frequency and length with speed are key parameters in animal locomotion research. They are commonly measured in a laboratory on a treadmill or by filming trained captive animals. Here, we show that a clustering approach can be used to extract these variables from data collected by a tracking collar containing a GPS module and tri-axis accelerometers and gyroscopes. The method enables stride parameters to be measured during free-ranging locomotion in natural habitats. As it does not require labelled data, it is particularly suitable for use with difficult to observe animals. The method was tested on large data sets collected from collars on free-ranging lions and African wild dogs and validated using a domestic dog.

KEY WORDS: Animal locomotion, Stride segmentation, Unsupervised machine learning

INTRODUCTION

Changes in stride frequency and length with speed are key parameters in human locomotion research (Maculewicz et al., 2016; Muro-de-la-Herran et al., 2014) and are routinely used in quadruped locomotion research (Heglund and Taylor, 1988; Jayne and Irschick, 2000; Smith et al., 2015; Sue et al., 2011; Witte et al., 2006). Measurement of these parameters enables the locomotor strategy used by an animal to attain a particular speed to be determined. They are commonly measured in laboratory-based experiments using a treadmill or by filming trained captive animals (Hudson et al., 2012; Williams et al., 2014). These approaches provide estimates for movement over uniform terrain with a constant velocity (steady locomotion) (Bertram, 2016). They are, however, not ideal for species that are difficult to handle or observe (e.g. lions or African wild dogs). Captive animals may not show the same locomotor characteristics as wild animals (Hudson et al., 2012; Williams et al., 2014) and treadmill locomotion can modify gait patterns (Blaszczyk and Loeb, 1993).

These limitations have been overcome by the development of animal tracking collars combining Global Positioning System (GPS) and inertial measurement units (IMUs) (accelerometers/gyroscopes) which can be sampled at high data rates (>5 Hz). The

detailed data these produce provide the potential to quantify how stride frequency and length vary with speed under natural conditions. In a typical deployment of several months, these collars capture large quantities of data (tens of thousands of strides), so to achieve realistic workloads an automated analysis system is required. Such a system needs to be able to remove periods of non-steady locomotion and segment the data into strides. Previous studies trained animals to move at steady speeds and removed non-steady locomotion by using a threshold based on speed (Maes et al., 2008) and velocity heading (Daley et al., 2016). Stride segmentation has been carried out using supervised machine learning (Mannini and Sabatini, 2012; Pfau et al., 2008). This method requires data to be collected while the animal is being viewed (labelled data) and this is challenging for difficult to observe wild species.

Clustering (unsupervised machine learning) is an exploratory approach that aims to find groups in data. It is ideally suited for use with the data collected from collars on difficult to observe animals as it does not require labelled data. This approach has previously been applied to characterise the behaviours of birds (Sakamoto et al., 2009) and humans (Trabelsi et al., 2013). To our knowledge, it has not been applied to the problem of stride segmentation in quadrupeds.

We developed an algorithm to estimate stride frequency and length during steady locomotion using a clustering approach. It was tested on large data sets collected from collars on African wild dogs (3290 strides) and lions (10,480 strides) and validated using a domestic dog.

MATERIALS AND METHODS

Data collection

Data were collected from two female adult lions, a male and a female African wild dog and a lurcher using custom-built Royal Veterinary College (RVC) GPS-enabled wildlife collars (Wilson et al., 2013) (Table S1). The lions and wild dogs are part of an ongoing study by the RVC and Botswana Predator Conservation Trust (BPCT) in Botswana (RVC CRERB 2013 1233 and a Botswana research permit EWT 8/36/4). MATLAB 2015a (Mathworks, Natick, MA, USA) was used for data analysis. The collars contained a GPS module and an IMU (Hubel et al., 2016). The current study used data from the highest resolution operating state (5 Hz GPS, 300 Hz accelerometer and 100 Hz gyroscope). The precision of the velocity and position data was improved by fusing GPS/IMU data with a Kalman filter (Wilson et al., 2013). Stride parameters were estimated from the Kalman-filtered GPS measurements and data from the y/z-axis accelerometers (Fig. 1I). Typical measurements from a wild dog are shown in Fig. 1A–C.

Pre-processing

The reaction to gravity measured by the accelerometers was removed using a 3rd order zero-phase (Oppenheim and Schaffer,

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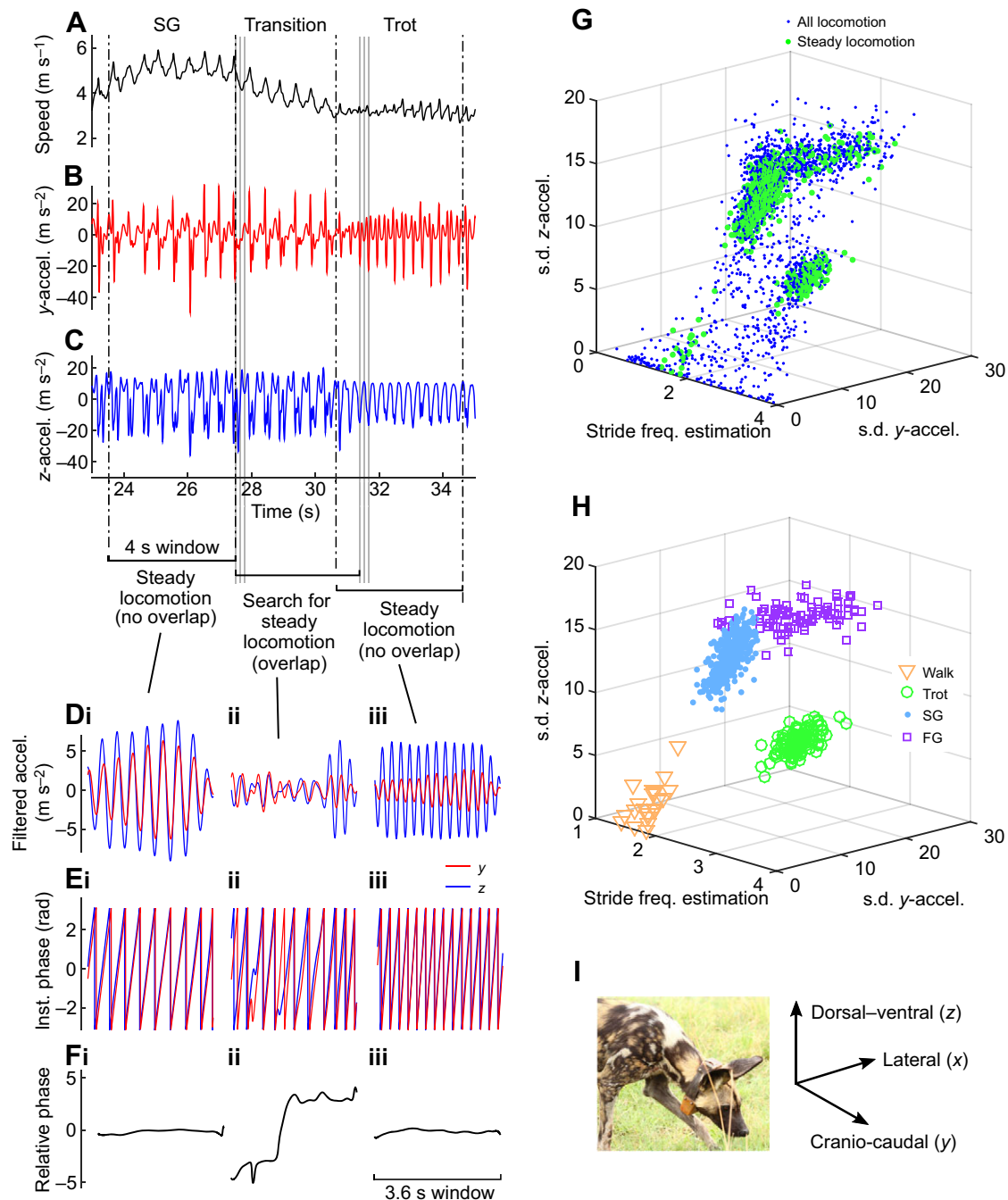


Fig. 1. Examples of the signals recorded by the animal tracking collar, steady locomotion detection and gait classification. Signals were measured from a free-ranging African wild dog (male). (A–C) GPS speed (A), and y -axis (B) and z -axis (C) acceleration (see I) measured during steady slow gallop (SG), the transition to a trot and steady trotting. The modified sliding window signal segmentation approach is shown beneath the plots in C. (D–F) Steady locomotion detection. (D) The results of filtering the windowed y - and z -axis accelerometer signals with a band pass filter (pass band ± 0.3 Hz around the stride frequency) for steady SG (i), the gait transition (ii) and steady trotting (iii). (E) The instantaneous phase of the filtered y and z accelerations. (F) The relative phases. The phase locking value (PLV) for steady SG and trotting is 0.984; the PLV for the gait transition is 0.802. (G) Feature space (calculated from multiple high sample rate recordings collected from African wild dog) for all locomotion types ($N=1992$, 4 s windows) and steady-state locomotion ($N=622$, 4 s windows). Features have been calculated from a 4 s window of data. (H) Result of k -means gait classification into walking ($N=21$, 4 s windows), trotting ($N=116$, 4 s windows), and slow (SG, $N=396$, 4 s windows) and fast (FG, $N=89$, 4 s windows) galloping clusters. Note the large separation between trotting and the other gaits and the clear distinction between the two galloping gaits. (I) Alignment of the three-axis accelerometer in the animal tracking collar.

2013) high-pass Butterworth filter (0.5 Hz cut-off frequency). The remaining signal was segmented using a sliding window approach (Fig. 1B,C). Windows (4 s long) were overlapped by 0.2 s (Fig. 1C) until steady locomotion was detected. Windows containing steady locomotion were not overlapped (Fig. 1C).

Steady locomotion

We assumed that there would be little variation in the phase difference between the signals from the y/z -axis accelerometers (over 4 s) during steady locomotion. The phase locking value (PLV) was used to provide a measure of phase synchronisation between the

two signals (Aydore et al., 2013):

$$\text{PLV} = \frac{1}{T} \left| \sum_{t=1}^T e^{i\Theta(t)} \right|. \quad (1)$$

PLV ranges from 0 to 1, with 1 representing the case where the relative phase (RP) between signals is identical and 0 when there is no phase synchrony. $\Theta(t)$ is the relative phase, T is the number of samples and t is each discrete sample. RP is:

$$\Theta(t) = \phi_y(t) - \phi_z(t), \quad (2)$$

where ϕ_y and ϕ_z are the instantaneous phases (IPs) of the windows of y - and z -axis accelerometer signals, respectively. IP was calculated using the Hilbert transform (Bracewell, 1999); as it is only meaningful for a narrow band signal, the windows of accelerometer signals were filtered (zero-phase, 5th order Butterworth bandpass filter; passband ± 0.3 Hz the stride frequency).

Transients introduced by the Hilbert transform were removed by extracting the middle 3.6 s of the windowed signal (Fig. 1D–F). Examples of bandpass-filtered accelerometer signals from a steady slow gallop, the transition to trot and steady trot are shown in Fig. 1D (i to iii, respectively). Fig. 1E,F shows the IPs and RPs of these signals. The phase synchronisation of the accelerometer signals during steady transverse gallop and trot can clearly be seen in Fig. 1Di–Fi and Diii–Fiii (PLV for both gaits is 0.984). The lack of synchronisation that occurs during the gait transition can be seen in Fig. 1Dii–Fii (PLV=0.521). A PLV threshold of 0.98 resulted in a balance between distinct clusters and retaining sufficient data (Fig. 1G, H). The total number of strides was reduced by 83% for the lurcher, by 44% and 47% for the two wild dogs and by 20% and 32% for the two lions. Fig. S1 and Table S6 allow comparison between the PLV method and the speed threshold method used in previous studies (Maes et al., 2008; Schmidt and Biknevicius, 2014).

Window stride frequency estimation

The stride frequency for a window of data was estimated from the z -axis accelerometer signal using an autocorrelation approach. The biased autocorrelation estimate (\hat{O}_{zz}) for a finite length (T) sampled signal is given by:

$$\hat{O}_{zz} = \frac{1}{T} \sum_{t=\tau}^T z(t - \tau)z(t), \quad (3)$$

where z is the window of data from the z -axis accelerometer and τ is the lag (samples). For a cyclic signal, such as that measured during locomotion (Fig. 1C), the autocorrelation coefficients peak at lags equivalent to the periodicity of the signal. The lag of the first positive peak in the autocorrelation coefficients was found to represent the stride period for galloping gaits and half the stride period for trotting and walking.

Clustering

To identify gait, clustering was performed on three features derived from the windowed accelerometer signals; features were selected using domain knowledge. The first two features were the standard deviation (s.d.) of the windowed y - and z -axis accelerometer signals, the third was the autocorrelation estimate of the stride frequency (Fig. 1G,H). Features were normalised to have zero mean and unit s.d. before they were clustered using the k -means algorithm.

The number of clusters was determined using the Davis–Bouldin criterion (Davies and Bouldin, 1979) and human inspection.

Stride parameters

Once the windows of data had been assigned a gait, it was possible to extract stride segments using the MATLAB peak find method. This enabled the individual stride frequency, length (GPS position data) and speed to be estimated. The vertical accelerations in each stride were registered using dynamic time warping (Ramsay and Silverman, 2005) so they were independent of speed; their magnitude was normalised to be between -1 and 1 . Statistical parametric mapping (SPM) and random field theory (RFT) were used to test for differences between registered stride traces (Pataky et al., 2013).

Validation

Validation was carried out by comparing stride parameter estimates from collar data measured on a male lurcher (moving freely off the lead) with those from video footage of the animal moving along a line at a range of speeds and gaits on a level playing field (RVC repository). Two video cameras were positioned parallel to the line (Hero3, GoPro Inc., San Mateo, CA, USA; 120 frames s^{-1} , 720×1280 pixels). Footage was calibrated using a 0.8 m-long stick placed on the line in front of each camera. To allow gait identification and calculation of stride parameters, we recorded the foot on/off events. Two symmetrical (lateral walking and trotting) and two asymmetrical (transverse and rotary gallop) gaits were identified using anteroposterior sequence analysis (Abourachid, 2003; Maes et al., 2008).

Lines were fitted to the stride frequency versus speed data and the stride length versus speed data for each method and gait using the least squares algorithm (Heglund and Taylor, 1988; Hudson et al., 2012; Wilson et al., 2013). The slopes of the linear regressions estimated from collar and video data were compared using analysis of covariance. Further validation was carried out by fitting lines to the stride speed estimates calculated from the stride length and frequency values versus the stride speed estimate from the Kalman-filtered GPS speed data. We assumed accurate parameter estimates would result in a line with a slope not significantly different from one.

RESULTS AND DISCUSSION

The variation of stride frequency and length with stride speed (collar data) for a lurcher, two wild dogs and two lions is shown in Fig. 2A–F. Stride frequency increased linearly with speed for the lurcher and lions within all gaits and for wild dogs during trotting and galloping but not during walking (Fig. 2A–C; Table S2). The rate of change of stride frequency decreased as the animal moved faster (Fig. 2A–C; Table S2). During galloping, stride frequency increased gradually with speed (Fig. 2A–C; Table S2). Our results are consistent with previous work (Heglund and Taylor, 1988; Maes et al., 2008). The lions used a lower stride frequency at a given speed than the smaller lurcher and wild dogs (Table S1). Stride length increased linearly with increasing speed (Fig. 2D–F; Table S2). This relationship has been found in other studies (Hudson et al., 2012; Maes et al., 2008).

Our method was validated against estimates from video data from the lurcher (Fig. 2G–N). The slopes and intercepts of the linear regressions estimated from the two methods were compared using analysis of covariance; no significant differences in slope ($P < 0.05$) were found (Table S3); the intercepts were significantly different ($P < 0.05$) (note the large data variability for stride frequency,

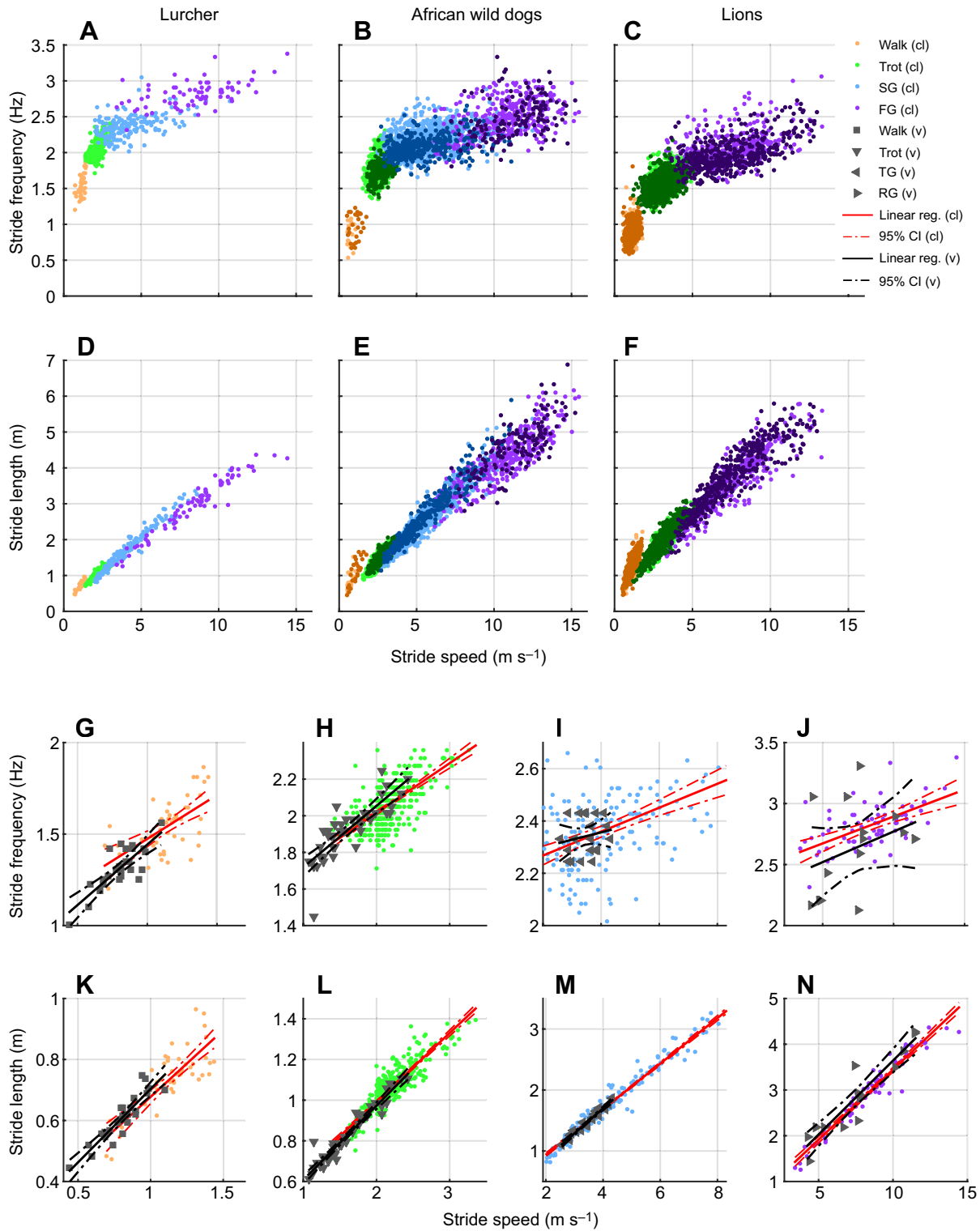


Fig. 2. Variation of stride frequency and length with speed for steady locomotion estimated from data collected using an animal tracking collar during walk, trot, and slow and fast galloping. (A–F) Stride frequency and length estimates for a lurcher (A,D), two African wild dogs (B,E) and two lions (C,F). Each point represents one stride. For the lurcher, $N=49, 392, 174$ and 76 for the walk, trot, slow gallop (SG) and fast gallop (FG). For the wild dogs, $N_1=19, 802, 1229$ and 321 and $N_2=26, 316, 430$ and 147 for the walk, trot, SG and FG. For the lions, $N_1=766, 3101$ and 385 and $N_2=1865, 3928$ and 435 for the walk, trot and gallop. (G–N) Comparison of stride frequency and length estimated from data collected using an animal tracking collar and from video footage for a lurcher. Note that stride parameter estimates from video data are calculated over individual strides. The anteroposterior sequence method was used to identify walking (G,K), trotting (H,L), SG (I,M) and FG (J,N) from video footage. Collar data were segmented into different gaits using the *k*-means algorithm. Linear regression lines are shown using solid lines, and 95% confidence intervals (CI) using dash/dotted lines. We found no significant difference between the slope of the lines fitted to the stride parameter estimates from collar or video data (analysis of covariance, $P>0.05$). The number of strides from the video footage for walk, trot, transverse gallop (TG) and rotary gallop (RG) gaits was 25, 41, 21 and 15, respectively. cl, data collected using an animal tracking collar; v, data from video footage.

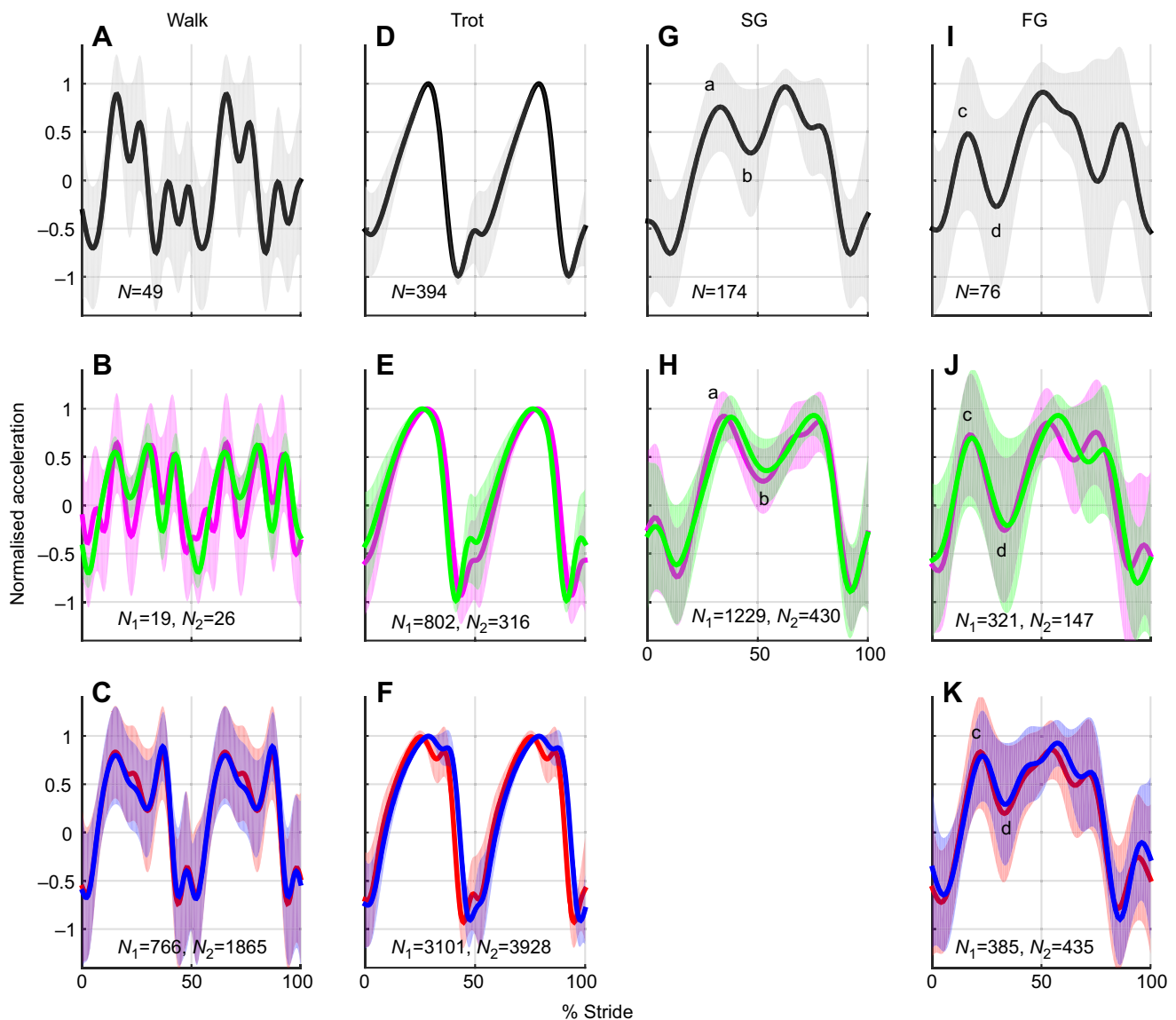


Fig. 3. Stride cut vertical accelerometer signals returned by the clustering algorithm. Data were recorded by an animal tracking collar. (A,D,G,I) Results from lurcher. (B,E,H,J) results from two African wild dogs (animal 1, N_1 , pink line; animal 2, N_2 , green line). (C,F,K) results from two lions (animal 1, N_1 , blue line; animal 2, N_2 , red line). The acceleration was normalised to be between -1 and 1 . The animal's gait was determined using the k -means algorithm. Slow and fast gallops are represented by SG and FG, respectively. The solid lines represent the average of the strides (N_1/N_2 values represent the number of strides). The variability of the signal is represented by plotting two standard deviations of the values (shaded region). Features used to distinguish between slow and fast gallops are marked a–d. Analysis using statistical parametric mapping and random field theory found significant differences between SG and FG traces at these locations and over the majority of the stride (Fig. S3).

Fig. 2G–J, and the low r^2 values, Table S3). While the range of speeds for each gait varies with the method used, they both return values that are reasonable compared with other work (Maes et al., 2008) and predictions from dynamic similarity (Heglund et al., 1974; Iriarte-Díaz et al., 2006). Dynamic similarity predicts that the walk to trot transition occurs at a Froude number between 0.5 and 1 and the trot to gallop transition occurs between 2 and 3 (Heglund et al., 1974; Iriarte-Díaz et al., 2006) (Table S4). Further validation was carried out by fitting regression lines to the GPS measured stride speeds and the stride speed predicted from stride length and frequency estimates obtained from GPS position data and accelerometer data (Fig. S2). The slopes of the lines were not significantly different from one ($P < 0.05$) (Table S5).

Fig. 3 shows the mean and 2 s.d. of the stride cut vertical accelerations for each gait and animal. The traces recorded during

trotting for all species are similar (Fig. 3D–F; visual comparison). The lower signal to noise ratio of the accelerometer signal during walking makes comparison between species difficult (Fig. 3A–C). The timing of the first positive and negative peaks in the traces for the slow (Fig. 3G,H; first positive peak marked by 'a', negative by 'b') and fast (Fig. 3I,J; first positive peak marked by 'c', negative by 'd') gallops in the dogs appears to be different. Analysis using SPM/RFT found significant differences ($P < 0.05$) between the traces at these locations and over the majority of the stride (Fig. S3).

As the collared animal does not have to be directly observed, our method reduces demands on field staff and equipment, and enables the study of free-ranging locomotion at self-selected speeds. It extends the range and number of species and habitats in which locomotion can be investigated, providing a tool to improve understanding of energetics, resource selection and the impact of

human intervention on animal populations. While it does not suffer the drop in performance associated with a surrogate approach (Campbell et al., 2013), it does require the correct number of clusters to be chosen. This simply requires a visual check and comparison with expected gait transition values (Heglund et al., 1974). Our results fit with previous observations (Biancardi and Minetti, 2012) that dogs perform transverse and rotary gallops at low and high speeds, respectively (Fig. 2A,D and B,E and Fig. 3G,I), and that lions perform a rotary gallop regardless of speed (Fig. 2C,F and Fig. 3K). It is unlikely, however, that our method would allow the separation of transverse and slow rotary galloping (Maes et al., 2008). Further work may enable other gait parameters, such as foot contact times, to be determined and this would allow finer gait classification and the ability to distinguish between transverse and slow rotary galloping. Our method could be extended to the classification of animal behaviour (Grünewälder et al., 2012), with the potential to reveal unseen behaviours (Brown et al., 2013), increase our understanding of elusive species and reduce observer effects.

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Competing interests

The authors declare no competing or financial interests.

Author contributions

O.P.D. and A.M.W. conceived and designed the study. O.P.D. analysed and interpreted the data and wrote the paper with extensive input from all authors.

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Supplementary information

Supplementary information available online at <http://jeb.biologists.org/lookup/doi/10.1242/jeb.146035.supplemental>

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