

Novel use of an activity monitor to model jumping behaviors in cats

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OBJECTIVE

To develop methods to identify and characterize activity monitor (AM) data signatures for jumps performed by cats.

ANIMALS

13 healthy, client-owned cats without evidence of osteoarthritis or degenerative joint disease.

PROCEDURES

Each cat was fitted with the same AM, individually placed in an observation room, then simultaneously recorded by 3 video cameras during the observation period (5 to 8 hours). Each cat was encouraged to jump up (JU), jump down (JD), and jump across (JA) during the observation period. Output from the AM was manually annotated for jumping events, each of which was characterized by functional data analysis yielding relevant coefficients. The coefficients were then used in linear discriminant analysis to differentiate recorded jumps as JUs, JDs, or JAs. To assess the model's ability to distinguish among the 3 jump types, a leave-one-out cross-validation method was used, and the misclassification error rate of the overall categorization of the model was calculated.

RESULTS

Of 731 jumping events, 29 were misclassified. Overall, the mean misclassification error rate per cat was 5.4% (range, 0% to 12.5%), conversely indicating a correct classification rate per cat of 94.6%.

CONCLUSIONS AND CLINICAL RELEVANCE

Results indicated that the model was successful in correctly identifying JUs, JDs, and JAs in healthy cats. With advancements in AM technology and data processing, there is potential for the model to be applied in clinical settings as a means to obtain objective outcome measures. (*Am J Vet Res* 2020;81:334–343)

Mobility, or the ability to move in one's environment with ease and without restriction, has been recognized as an important facet of quality of life in humans¹ and, more recently, in companion animals.² Mobility alterations and changes in activity levels have been reported in various companion animal conditions including dermatitis,³ surgery recovery,^{4,5} stress,⁶ and OA.^{7–10} Yet, for companion animals, there is a general lack of validated refined approaches for the assessment of mobility and activity.

To our knowledge, there are no reliable outcome measures to evaluate chronic pain in cats and only 2

medications, robenacoxib and meloxicam, approved outside of the United States and none in the United States for treating chronic pain in cats. In humans, joint pain often results in decreased physical activity.^{11,12} Osteoarthritis and DJD are common sources of signs of pain in older cats,¹³ clinically affecting approximately 22% (63/292)¹⁴ to 34% (74/218)¹⁵ of cats, and radiographic evidence of DJD is apparent in approximately 90%¹³ of cats. In addition, physical activity is expected to be altered by OA and DJD and is a proposed end point for assessing efficacy in treatments targeting signs of chronic pain in cats. In clinical trials, owner questionnaires have been used in an attempt to capture data regarding these changes.^{7,16–19} However, signs of chronic pain are often associated with behavioral changes that develop slowly over time, and these subtle changes are often challenging for owners to detect. Therefore, the subjective nature of owner questionnaires creates issues of reliability^{15,16,20–22} and bias.²³ Accordingly, objective end points are needed to better evaluate mobility and activity, aiding in assessing efficacy of analgesic treatments in cats with signs of pain.

ABBREVIATIONS

AM	Activity monitor
CV	Cross validation
DJD	Degenerative joint disease
FDA	Functional data analysis
JA	Jump across
JD	Jump down
JU	Jump up
LDA	Linear discriminant analysis
MER	Misclassification error rate
OA	Osteoarthritis

Recently, AMs have been used to objectively measure body movement in humans^{24–27} and in clinical trials involving treatments targeting OA-related signs of pain in cats.^{7,10,18,22,28–30} In addition, AMs have been successfully used in detecting differences in changes in activity for treated versus untreated cats with signs of OA pain.^{18,29,31} However, in comparisons of activity during baseline, placebo, and treatment, conflicting results have been reported⁷ as have inconsistencies between owner assessments and AM measurements.^{18,29,30} To our knowledge, only 1 study,^a involving use of an NSAID in a parallel group design, shows agreement between results from AMs and owner surveys. In addition, AM data for companion animals are often recorded at coarse scales (eg, total activity over 1- to 5-minute periods, known as epochs) and summed or averaged over days or weeks, representing a limited quantification of activity over time.

Alterations in specific behaviors have been associated with signs of chronic pain and are reflected in results from clinical questionnaires (eg, client-specific outcomes measure and feline musculoskeletal pain index^{7,18,31}) that require owners to identify movements or activities that their cats have trouble performing. Movements that owners and veterinarians identify as being altered by signs of pain include jumping, stair climbing, and grooming.^{15,20,32–34} Specifically, reductions in jumping activity in cats with OA are most commonly described, with 68% (19/28) to 71% (20/28) of owners reporting that their cats had alterations in jumping activity.³²

The ability to objectively identify and quantify these clinically relevant movements (jumping, climbing, and grooming) could improve diagnosis of underlying causes of signs of pain in cats and our ability to accurately assess treatment efficacy. Typically, AM data are recorded at a time resolution incompatible with detecting specific activities or movements (eg, jumps) of short duration (eg, approx. 0.5 sec). To identify such short duration movements, AM data must be recorded at a high resolution. In addition, because of the large quantities of data involved when monitoring moving animals, methods to recognize and quantify movements of interest and filter movements of noninterest (considered noise) are required. Therefore, the objective of the present study was to develop methods to identify and characterize AM data signatures for jumps performed by cats. We focused on characterizing jumping activities for healthy cats as an initial step in developing an effective statistical model for potential clinical use in cats with disease.

Materials and Methods

Animals and inclusion criteria

Client-owned cats were eligible for the study if they were healthy, had no evidence of OA or DJD on physical examination, and were not receiving any concomitant medication. For each cat, body weight

and body condition score (on a scale from 1 to 9) were assessed during the initial veterinary examination. Cats were recruited from those owned by university-associated personnel, and written informed owner consent was obtained for each cat enrolled. Our study was conducted under the North Carolina State University Institutional Animal Care and Use Committee approval 18-059-O.

Laboratory setting

Each cat was observed for 1 day in a laboratory setting. During the day of observation, a single cat was housed in a purpose-designed observation room (3.1 m long X 2.9 m wide X 3.6 m high; **Figure 1**) that had a linoleum tile floor. Cats had access to a litter box, water, bedding, and enrichment items, including a cat toy and a ping-pong ball. The room also had 2 jumping surfaces (each constructed of matte sheet metal [1.0 X 0.5 m] and 0.7 m from the floor) and a set of portable stairs (3 steps with 30 X 76 cm treads and 30-cm risers) with foam-pad covering. One ceiling-mounted and 2 wall-mounted (approx 1.2 m from the floor) digital video cameras^b collectively recorded the entire room.

Data collection

Each cat wore a 1.3-cm-wide collar with the same AM^c (set to record in raw data collection mode at 32 Hz [1 observation/0.03125 seconds]) attached and positioned under the neck during the observation period, which began after an acclimation period (approx 1 hour) in the observation room. All observations were obtained between 08:00 AM and 5:00 PM, yielding approximately 5 to 8 hours of continuous data from each camera and the AM. At points throughout the observation periods, a veterinary technician used treats and toys to encourage cats to JU, JD, and JA the jumping surfaces. Record-

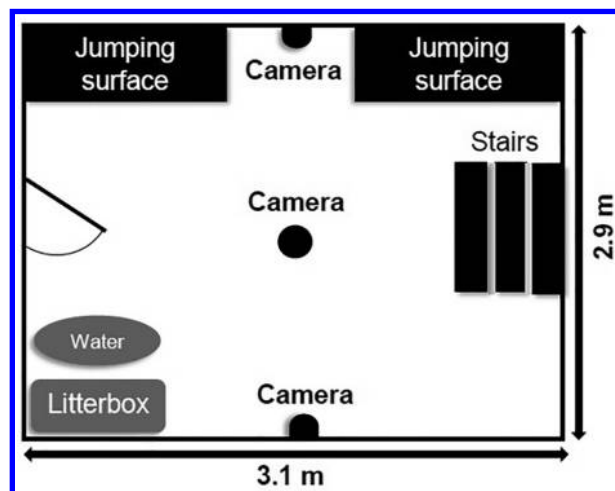


Figure 1—Schematic of the purpose-designed observation room used to individually record (video and AM) jumping events of 13 client-owned cats that were healthy, had no evidence of OA or DJD, and were not receiving any medications.

ings from the AM and cameras were synchronized with a computer clock.

Following the observation period for each cat, data from the AM were downloaded with the manufacturer's software^d into a spreadsheet,^e and the video files were downloaded^f and saved for subsequent viewing. Data for each individual cat were recorded as time series spanning the entire observation period. Each numeric observation represented movement in the form of acceleration on an integer-valued scale from -128 to 127. These values were directional (corresponding to either a positive or negative rate of change in velocity) and proportional to the amount of acceleration but were generic and not associated with specific units of acceleration. In addition to activity values, metadata collection included cat identification, date, and start time. Video files included an on-screen display of date and time, enabling synchronization with the AM data.

Event identification

Digital video recordings of each cat were viewed by a trained observer (KPS), and jumping events (JAs, JDs, and JUs) were timed and manually labeled, thereby matching the time stamp on the AM and video outputs. Instances of variations in jumping events (eg, when the monitor was displaced on the side of a cat's neck) were noted. For each jumping event, a continuous series of activity measurements was labeled, beginning with the initiation of the jump and ending with the landing. For each video-confirmed jumping event, the time point for the beginning of the event was identified in the AM output by the time stamp, and the change from baseline (magnitude > 10 units) corresponded to the force associated with the jump initiation. The end of the event was identified by observing the activity values returning to approximately 0, corresponding to the completion of the forces associated with the jump. Events were excluded if they occurred when the AM was determined to have been displaced (ie, flipped upside down). Personnel in the observation room watched for AM displacement, and ≥ 1 of the 3 video cameras was anticipated to capture such AM displacement. The jumping events data for each cat were stored in a file for analysis.

Statistical analysis

Raw and scaled data for jumping events were evaluated. For scaled data, the time variable, t , for each event for each cat was scaled to the duration unit interval of 0 (event start) to 1 (event end) before analysis. Functional data analysis was used to fit the event data, followed by LDA to reduce dimensionality and to classify events into 1 of the 3 jump types: JAs, JDs, or JUs. Subsequently, CV was applied to assess how well the proposed model classified new events. Gaussian kernel density was estimated for the frequency distribution for each of the 3 jump types. All statistical analyses were performed with available software.^{g-i}

FDA—Each jumping event was represented by raw data of activity observations taken automatically at discrete subintervals (every 1/32 second), resulting in a time series of several measured values, denoted by $x_j(t)$ for the j th event. The number of values recorded varied from event to event, depending on duration, with each event consisting of $q + 1$ observed activity values, where q was the number of subinterval 1/32-second time slices of the particular event. The time variable t was scaled so that the range of t was always $0 \leq t \leq 1$. The values for each event changed over the duration of the event, yielding curvilinear data signatures. The time series were functional observations that were then characterized and analyzed with available FDA software.ⁱ The underlying predictive model for the j th event was given by the spline equation:

$$x_j(t) = \sum_{k=1}^K c_{jk} \phi_k(t)$$

The basis functions used were B-splines,^{35,36} which are smooth piecewise-continuous cubic polynomials defined over $0 \leq t \leq 1$ and commonly applied when modeling aperiodic data and are uniquely determined from n prespecified subintervals ($0 = t_0 < t_1 < \dots < t_n = 1$) that partition the range of t . The set of t_i values, called a knot sequence or set of breakpoints, specified where the piecewise polynomials were joined. The selection of n and the t_i values were arbitrary but chosen in light of the anticipated behavior of the time series being approximated, and these values affected the acceptability of the fitted spline curve. We spaced the knot sequence uniformly. A B-spline basis was constructed with available FDA software.ⁱ With this model, the resulting continuous function $x(t)$ closely approximated the observed discrete time series with a small number of components.

The method of penalized least squares was used to estimate the K coefficients $\{c_{jk}\}$ for event j . In general, this was accomplished for each jumping event by calculating the coefficient vector $\mathbf{c}$ as the matrix product with the following formula:

$$\mathbf{c} = (\Phi^T \Phi + \lambda \mathbf{R})^{-1} \Phi^T \mathbf{y}$$

where $\Phi = \{\phi_k(t)\}$ was an $n \times K$ matrix of the basis functions evaluated at the knots, λ was a smoothing parameter (set to 10^{-5}), and $\mathbf{R}$ was a $K \times K$ penalty matrix based on the second derivatives of the basis functions (superscript T denoted the matrix transpose). The larger the λ , the more overall smoothing occurred. Ordinary least squares, which occurs when $\lambda = 0$, is a special case in which the underlying model matrix equation expands to the following formula:

$$\begin{bmatrix} y_0 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} \phi_1(t_0) & \phi_2(t_0) & \dots & \phi_K(t_0) \\ \vdots & \vdots & & \vdots \\ \phi_1(t_n) & \phi_2(t_n) & \dots & \phi_K(t_n) \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_K \end{bmatrix}$$

where y_i ($i = 1, \dots, n$) represented the observed activity value at time t_i , and $\phi_k(t_i)$ was the evaluation of

the k -th basis function at time t_i . For each event, a solution for c and predicted values ($\hat{y}_i$) were calculated with available software.¹ Ultimately, the K coefficients estimated for each event statistically characterized the jump and were then used in the LDA classification method.

LDA—Once all 3 types of jumping events (JAs, JDs, and JUs) were individually characterized for all cats in terms of estimating the K B-spline coefficients for each event, LDA was used to further reduce the dimensionality of jump characterizations and to provide a mechanism for classifying new unknown events as to type of jump. In this method, each event produced K estimated coefficients (c_k) that served as a single multivariate observation for the LDA. Taken altogether, the various events from all 3 jump-type series provided n_1 , n_2 , and n_3 observations for jumps of types JA, JD, and JU, respectively. There were $N = n_1 + n_2 + n_3$ observations total, and these could be thought of as points in K -dimensional space, with each observation associated with 1 of the 3 event types. A second subscript m was attached to identify each individual cat, where $m = 1, \dots, M$. Thus, for cat m , there were $N_m = n_{1m} + n_{2m} + n_{3m}$ total jumps recorded. The complete data set of N observations was assessed³⁷ with available LDA software.¹

With LDA, we attempted to differentiate among the 3 jump types (JAs, JDs, and JUs) by identifying transformations that maximized the distances between the group-level mean vectors (centroids or centers of mass of the data points), resulting in well-defined geometric regions associated with each jump type. The LDA was considered successful when the points for each jump type were closely congregated around the respective jump-type mean and were not too close to the means of the other jump types (ie, the within-group variances were small relative to the among-group variances).

The sample between-groups covariance matrix was defined³⁸ with the following formula:

$$B = \sum_{g=1}^G (\bar{x}_g - \bar{x})(\bar{x}_g - \bar{x})^T$$

where G was the number of groups ($G = 3$ [ie, JA, JD, JU]), $\bar{x}_g$ was the sample mean vector of the g th group based on n_g observations, $\bar{x}$ was the mean vector of the G sample mean vectors, and the dimension of each vector was equal to K (the number of coefficients from the FDA). The sample within-groups covariance matrix was defined as:

$$W = \sum_{g=1}^G \sum_{p=1}^{n_g} (x_{gp} - \bar{x}_g)(x_{gp} - \bar{x}_g)^T$$

where x_{gp} was the p th observation vector in the g th group.

The LDA method was used to classify observations on the basis of use of prior probabilities of jump-type group membership that factored into calculating posterior probabilities. The prior probability P_g reflected the likelihood of a random observation being from jump-type group g without regard to the observed data, whereas the posterior probability reflected the likelihood of an observation being from jump-type group g given the data. A jumping event was classified into the jump-type group with the largest posterior probability, minimizing the total probability of misclassification. Given that the relative frequencies of the jump types observed in our laboratory setting may not have reflected the frequencies that could have occurred in cats' home environments, equal prior probabilities were used to avoid a priori biasing. Available software¹ was used to classify new observations during the CV step. The LDA method generated 2 linear discriminant values (LD1 and LD2) for each jump event from the respective coefficients derived from the FDA method. For each event, a point represented by LD1 and LD2 was plotted in a 2-D density plot. Resulting clusters (or groups) were further defined by 90% elliptical density regions.

CV—The capability of the fitted model to correctly classify jumping events was assessed with CV. With this approach, a statistically valid estimate of the prediction error rate was obtained by use of a subset of the data to fit the model and then evaluate how well it classified the remaining events not used in the fitting. We used a cat-based leave-one-out CV approach³⁹ in which, of M cats, the data from cat m were singularly removed (test set), and the data for the remaining $M - 1$ cats (training set) were used to fit the FDA model. Then, the events for cat m were classified as to jump type with the LDA method, with the prior probability set at 1/3 for each jump type. Misclassification was defined as a known event type (eg, JD) classified as some other type (eg, JU or JA). The proportion of events that were incorrectly classified was tallied relative to the total number of jumps N_m observed for cat m . This proportion was defined as the MER for cat m or MER_m . In other words, the MER was derived for each cat by dividing the number of incorrectly classified events by the total number of observed events for that cat. This process was repeated for each cat in turn ($m = 1, \dots, M$). The results were summarized to reflect overall performance accuracy by calculating the model MER as the mean of the MER_m values, which equally weighted the data per cat. A weighted MER for each jump type was calculated by dividing the total number of misclassified events in a jump type by the total number of events classified as that jump type. Additional summary statistics specific to the types of misclassification were produced for each cat.

Another statistic analogous to a traditional CV statistic was calculated similarly to the overall MER, except that it was based on removing data of the m th

cat, then classifying all values in the data set. Such MER values were denoted by MER_m^* and MER^* .

Results

Animals

Thirteen healthy client-owned cats that had no evidence of OA or DJD and that were not receiving any medication were recruited for the study; all 13 cats were eligible and enrolled. For these cats, age ranged from 2 to 13 years, body weight ranged from 3.3 to 6.6 kg, and body condition scores ranged from 5 to 8 (on a scale from 1 to 9). There were 10 domestic shorthair cats and 2 Bengal cats. There were 6 castrated males, 4 sexually intact females, and 3 spayed females.

Jumping events

The total duration of personnel interaction with each cat during the observation period ranged from approximately 2 to 4 hours, with 5 to 10 interactions/cat, and each interaction lasted 30 to 60 minutes. For each cat, the observation period was 5 to 8 hours and included approximately 576,000 to 921,600 activity values/cat. Overall, there were 754 jumping events recorded and identified; the median number of jumping events per cat was 43 (range, 17 to 191). Twenty-three of the 754 (3.1%) jumping events were removed because of AM displacement. These 23 excluded events (15 JDs and 8 JUs) represented jumps by 6 cats, with 1 cat having had 11 excluded jumping events. For jumping events during which the AM was observed to have been flipped upside down, the re-

sulting jump signature appeared to be inverted, compared with similar jumps performed with the AM in proper orientation. Of the remaining 731 jumping events, 294 JDs, 300 JUs, and 91 JAs were included in analyses.

Raw activity values represented generic values of acceleration or movement by individual cats (**Figure 2; Table 1**). The range of values for JUs, JDs, and JAs were -40 to 30, -44 to 37, and -31 to 23, respectively. The positive and negative values indicated directional accelerations aside from gravity, with a value of 0 indicative of no acceleration (eg, in a resting state). Kernel density estimation for the frequency distribution of the duration of the 731 jumping events (300 JUs, 294 JDs, and 91 JAs) was graphed (**Figure 3**), and the median durations of JUs, JDs, and JAs were 0.434 seconds (range, 0.188 to 0.563 seconds), 0.344 seconds (range, 0.219 to 0.594 seconds), and 0.688 seconds (range, 0.438 to 1.094 seconds), respectively. The 25th and 75th percentiles of duration were 0.406 and 0.469 seconds for JU, 0.313 and 0.375 seconds for JD, and 0.633 and 0.750 seconds for JA. All jumping events were scaled in duration from 0 (event start) to 1 (event end) prior to analysis. Durations and scaled signatures of the same jump types were similar across cats. Jump signatures within cats were repeatable, although some within-cat variation was observed; at least 1 cat's JU signatures appeared to change slightly during the observation period.

FDA

For FDA, the knot sequences were set at values of 0, 0.25, 0.50, 0.75, and 1. These internal break-

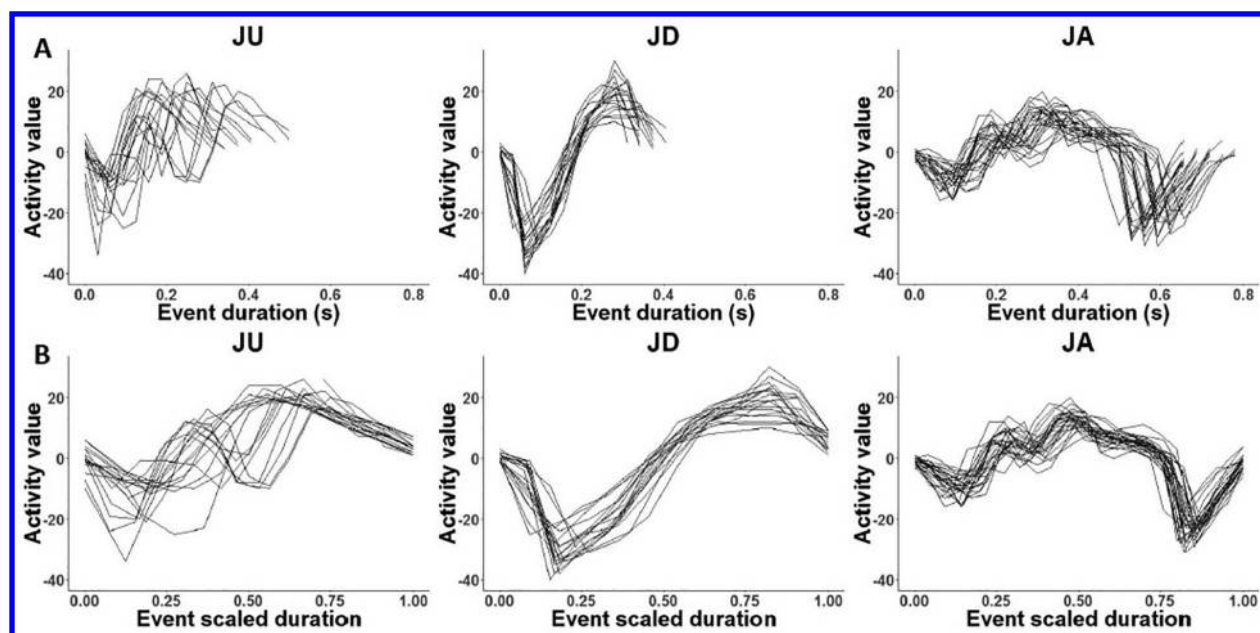


Figure 2—Representative graphs of raw activity values recorded by an AM before (A) and after (B) scaling the duration of jumping events of one of the cats described in Figure 1 to the unit interval from 0 (event start) to 1 (event end). Change from baseline (magnitude > 10 units) corresponded to the force associated with the jump initiation. The end of the jump event was noted as when the activity values returned to approximately 0, corresponding to the completion of the forces associated with the jump.

Table 1—Representative time series of raw data recorded with the AM for an identified jump event that occurred during the observation period of 1 of 13 healthy client-owned cats that had no evidence of OA or DJD and was not receiving any medication. Change from baseline (magnitude > 10 units) corresponded to the force associated with the jump initiation. The end of the event was identified as when the activity values returned to approximately 0, corresponding to the neutralization of the forces associated with the jump.

Epoch*	Elapsed duration (ms)†	Time	Raw activity value‡	Jump type
1097871	31.25	31:49.0	0	—
1097872	62.50	31:48.5	1	—
1097873	93.75	31:48.5	1	—
1097874	125.00	31:48.6	3	—
1097875	156.25	31:48.6	7	—
1097876	187.50	31:48.6	7	—
1097877	218.75	31:48.7	0	JU
1097878	250.00	31:48.7	−4	JU
1097879	281.25	31:48.7	−13	JU
1097880	312.50	31:48.7	−27	JU
1097881	343.75	31:48.8	−24	JU
1097882	375.00	31:48.8	6	JU
1097883	406.25	31:48.8	9	JU
1097884	437.50	31:48.9	10	JU
1097885	468.75	31:48.9	13	JU
1097886	500.00	31:48.9	14	JU
1097887	531.25	31:49.0	20	JU
1097888	562.50	31:49.0	18	JU
1097889	593.75	31:49.0	12	JU
1097890	625.00	31:49.1	7	JU
1097891	656.25	31:49.1	3	JU
1097892	687.50	31:49.1	−3	—
1097893	718.75	31:49.2	−6	—
1097894	750.00	31:49.2	−8	—
1097895	781.25	31:49.2	−3	—
1097896	812.50	31:49.2	0	—
1097897	843.75	31:49.3	−2	—
1097898	875.00	31:49.3	−2	—

*Each epoch represents a data collection point of 0.03125 seconds. †Milliseconds were summed over the duration of recording. ‡Values were directional and proportional to the amount of acceleration but were generic and not associated with specific units of acceleration.

— = The activity was not considered a jumping activity.

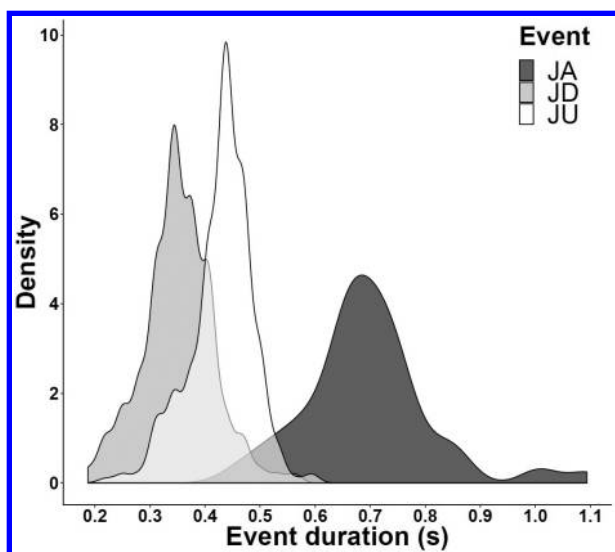


Figure 3—Kernel density estimation (with Gaussian kernel) for the frequency distribution of the durations of 731 jumping events (294 JDs, 300 JUs, and 91 JAs) performed by the cats described in Figure 1.

points were selected because of their fit with jump signatures. For example, with only 3 breakpoints, the JA characterization missed variation in the jump signature and did not resemble the original pattern, whereas with > 5 breakpoints, the data appeared to be overfitted, again not resembling the original signature. The number of basis functions (K) produced was equal to the sum of the order of the B-splines (4 for cubic polynomials) and the number of interior knots (3 in the present study), so that K was 7 here. Thus, a set of 7 coefficients was produced with the FDA method for each jumping event, characterizing the pattern of each event (**Figure 4**). With 7 coefficients for each of 731 jumping events, 5,117 coefficients were used in the subsequent analysis.

LDA

From the coefficients determined with FDA for each jumping event, LDA was used to generate 2 linear discriminant values (LD1 and LD2) for each respective jumping event. A point represented by LD1 and LD2 for each event was recorded in a 2-D popula-

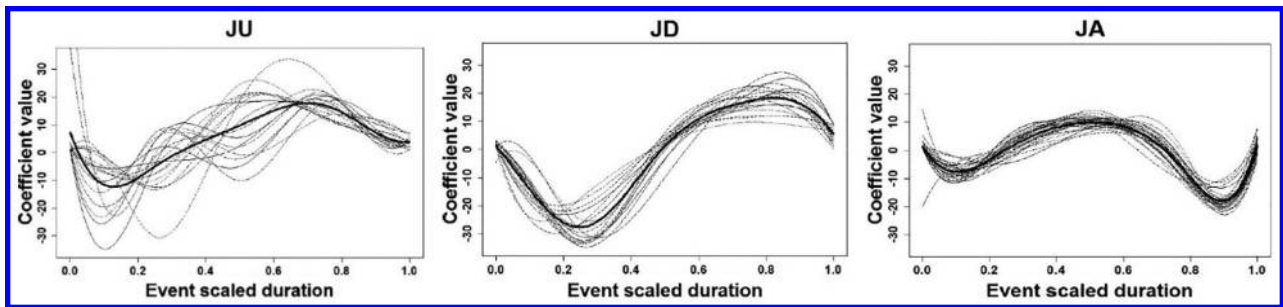


Figure 4—Representative results of FDA characterization of the jumping events of one of the cats described in Figure 1, with the duration of events scaled to an interval from 0 (event start) to 1 (event end). The bold line represents the mean FDA fitted B-spline curve of each respective jump type for the cat.

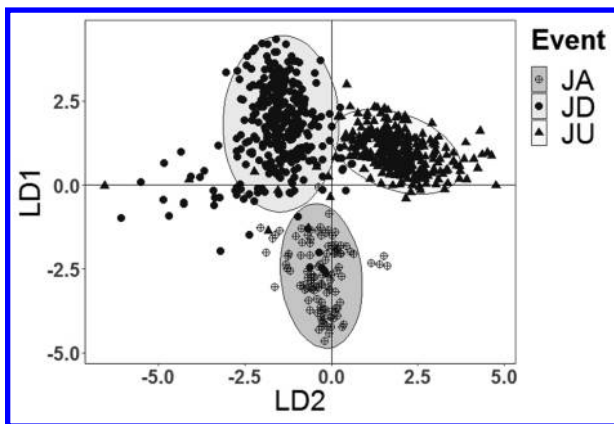


Figure 5—The 2-D population density plot of LDA results for all 731 jumping events for the cats described in Figure 1. The circles with crosses represent JAs, the solid circles represent JDs, the triangles represent JUs, and each outlined shaded region represents the 90% elliptical density region for the respective jump type.

tion density plot. From the event coefficients determined in FDA, results of LDA yielded 3 population clusters (or groups), 1 for each jump type (**Figure 5**). Each jump-type population cluster was then further defined by a 90% elliptical density region.

CV

The classification model was evaluated with the leave-one-out CV method by removing 1 cat's data at a time so that the model could be used to predict each cat's individual events. Prior probability was set at 1/3 for each jump type. Of 731 jumping events, 29 were misclassified: 12 JDs as JUs, 11 JUs as JDs, 5 JDs as JAs, and 1 JA as JD (**Table 2**). Overall, the mean MER was 5.4% (MER range, 0% to 12.5%), conversely indicating a correct classification rate of 94.6% for jumping events. The alternative MER* (calculated on the basis of removing the *m*th cat's data and then classifying all values in the data set) was 3.6%, conversely indicating a correct classification rate of 96.4% for jumping events. When considered on the basis of jump type and an equal prior probability of each jump type, the weighted MER was 3.6%, 5.5%, and 0.9% for JUs, JDs, and JAs, respectively.

Discussion

The ability to objectively monitor changes in clinically relevant body movements or activities is desirable for diagnosis of conditions impacting mobility and efficacy of treating such conditions in companion animals. Pruritic behavior in dogs has been identified by AMs⁴⁰; however, detecting daily activities with AMs has not been described in dogs or cats. Accelerometers have been used to detect lameness⁴¹ and monitor lying time⁴² in cattle. In humans, number of steps⁴³ and duration of sitting and standing⁴⁴ have been used to assess postsurgical recovery. Accelerometers have also been used successfully to distinguish certain daily activities in wild animals, such as pumas (walking, running, and grooming),⁴⁵ badgers (walking, running, and foraging or eating),⁴⁶ baboons (walking, running, grooming, and foraging or eating),⁴⁷ beavers (walking, swimming, grooming, and foraging or eating),⁴⁸ and penguins (swimming).⁴⁹ Of note is the fact that the accelerometers used in wild animals are larger, making them difficult to place on a cat or dog, and many of the monitors are not commercially available. In the present study, however, the AMs were size- and weight-appropriate for cats, commercially available, and successfully used in detecting jump events. Still, additional considerations, such as the frequency of data capture, are important when attempting to record short duration movements, such as JUs and JDs that for the height evaluated in the present study lasted < 1 second. The AM used in the present study recorded data at 32 Hz, and the manufacture's software allowed us to access the raw activity values, which were imperative for the analyses we needed to perform. In addition, the AM we used has been shown to be more sensitive to accelerations in the vertical direction⁵⁰; however, separate trajectory planes (x, y, and z) were not reported. The magnitude of change from baseline (corresponding to the force associated with the jump initiation) differed among different jump types. The accelerations associated with JUs or JDs were more focused in 1 direction (up or down, respectively) resulting in more extreme values. Jumping across likely required less effort and produced accelerations in both the x- and y-planes, potentially resulting in smaller activ-

Table 2—Summary results of leave-one-out CV analysis to assess the capability of the combined FDA and LDA fitted model to correctly classify jumps by type (JUs, JDs, or JAs) on the basis of AM-derived data, compared with the actual video-confirmed types of jumps observed for the cats described in Table 1.

Actual jump type*	Model-classified jump type			Weighted MER†
	JU	JD	JA	
JU	297	11	0	0.036
JD	12	292	5	0.055
JA	0	1	113	0.009

*Video-confirmed jump type. †Calculated as the number of misclassified events in a jump type divided by the total number of events for that jump type.

ity values. The AM we used may have processed the acceleration data in a way that was not cumulative in directional acceleration, or it may have been less sensitive in one plane than another, depending on the orientation of the AM. Despite this, the methods used in the present study were capable of distinguishing between JUs, JDs, and JAs. However, when the AM was flipped upside down during a jump, the resulting jump signature appeared inverted, compared with similar jumps performed with the AM in proper orientation. This situation potentially could be identified in data derived from a home setting by use of a screening algorithm, which was unnecessary in the present study because we excluded jumping events for which the AM was displaced. Although flipped monitors occurred in only 3.1% (23/731) of the jump events in the present study, this problem would likely be reduced or eliminated by improving fitment (eg, by use of a thicker or wider collar). If such improvement did not completely eliminate the displacement issue, some jumps would be missed in the home setting. However, this would not be expected to result in a substantial loss of data because such displaced AMs could be physically reoriented to the correct position by the client. We suspect that in the near future, technological developments will allow AMs to be built into collars, likely mitigating this problem. The potential for AM displacement is important to keep in mind when such devices are used outside of a laboratory setting, where video confirmation is not available.

Although reduced activity often occurs with chronic pain and increases in activity are interpreted as a surrogate for a reduction of pain, such interpretations must be approached with caution. For example, dogs with OA had increased nighttime activity measured by AMs.⁵¹ This increase in activity (eg, potential sign of restlessness) could be misinterpreted as a reduction in pain. In addition, variation in cats' activities has been shown to be influenced by time of day, day of the week, and housing (indoor or outdoor).^{10,28,52,53} These issues are exacerbated by coarse recording frequencies and data reduction techniques that make interpretation of overall activity more difficult and conclusions possibly less accurate. There-

fore, more refined methods to assess mobility and activity as indicators of pain are desired. Physical activity has increasingly been recognized as relevant in many aspects of health, and, recently, novel statistical methods have been used in companion animals to reveal more detail from AM data than just sums or averages. For instance, FDA was used to characterize movement patterns and detect behavioral characteristics of cats with versus without OA,²⁸ and a hidden semi-Markov model was used to categorize activity levels in cats with OA treated for signs of pain.^k However, to our knowledge, the present study was the first to evaluate the usefulness of an AM in identifying specific jumping movements in cats.

In addition, the prior probabilities of each jump type were specified as equal, so as not to bias the classification algorithm used in the present study. The relative frequencies of jumps in laboratory settings will not necessarily reflect the natural order in home environments, and we suspect that these frequencies will prove to be different following data collection from animals in home settings and without movements encouraged by a human. Characterizing more empirical jumping events would provide additional information that could enhance our understanding of cat behavior. Incorporating home-environment prior probabilities for jump types in LDA could improve the classification rates.

The present study focused on characterizing jump signatures in healthy cats to determine whether it was possible to model such activities in cats. Results of the present study supported the usefulness of the model in cats. A natural extension is to apply similar models to cats showing signs of pain. If jumping signatures are different between healthy cats and cats with signs of pain, both quantitative and qualitative aspects of jumps could be informative in clinical trials. In addition, application in home environments would provide data on events beyond jumps; however, we believe that jumping activity will be a central and perhaps sufficiently relevant activity that could be monitored as a surrogate pain status in cats. Nonjumping events were not evaluated in the present study; however, when manually annotating data, jumping signatures were found to have been distinct, compared with other movements recorded (eg, scratching, stair climbing,

grooming, walking, trotting, and headshaking). Data recorded for such other activities would not likely be confused with jumps, partly because of the intensity or repetitiveness of the nonjumping activities. Additionally, in the present study, all jumps were performed on surfaces of uniform height and width, and further research is needed to determine the extent to which height or distance influences jumping signatures obtained with AMs. If such differences exist, they may allow quantitative measure of jump height, in addition to jump frequency, to be determined from AM data. It is particularly important to evaluate the performance of the proposed method for characterizing jumping behavior and other activities with data collected in home environments.

In the present study, some cats jumped more readily in response to encouragement, whereas others seemed more hesitant, resulting in some cats performing more jumps than others. The greatest number of jumps by a cat was approximately 11 times that of the cat with the fewest jumps. Different jumping techniques and trajectories were apparent between and, at times, within cats, whereas some cats crawled down slightly before a jump. Although these factors all likely influenced jump duration, our results indicated that the durations and scaled signatures for the same jump types were similar across cats and that our model was reliable in predicting the jump types across cats.

When applying the model of the present study to clinical trials, patient selection would be important. Recruitment may include animals with different home environments, including available jumping surfaces or access to the outdoors. Furthermore, some cats may naturally jump more than others. To avoid bias, patient selection and treatment allocation approaches account for possible high cat-to-cat variability, owing to a number of factors including different degrees of disease. For clinical studies that use jumping behavior as an end point, we recommend consideration of crossover study designs to reduce bias and sample size and increase efficiency.

Future research should include characterization of jump signatures in cats with signs of pain as well as testing the proposed characterization model in cats in home environments. For example, differences in jumping signatures for cats with versus without OA could be clinically valuable. Our findings indicated that the FDA and LDA methods we used were reliable in characterizing and distinguishing between jump types in cats in the laboratory setting. However, data-filtering techniques will be required to use similar methods in clinical settings because identifying jumping events manually with the help of video recordings, as done in the present study, would not likely be feasible in client-owned home environments nor necessarily practical for future laboratory studies. Therefore, approaches that identify and extract events of interest from raw time series data are needed to expedite the classification process.

Results indicated that the current model was reliable in correctly identifying jumping events in healthy

cats of the present study. Future work in developing preprocessing methods to apply to AM data collected in cats is warranted. An ability to detect specific jumping behaviors would be of great benefit in assessing efficacy of analgesic treatments in cats. The approach is expected to be applicable to cats with signs of pain, including those with OA or DJD, and should be useful in identifying new objective end points to assess treatment efficacy. Further, if the signatures of jumping events differed for cats with versus without signs of joint pain, then frequency and normality of jumping events could be used in combination for early detection of OA or other underlying causes of joint pain in cats.

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Footnotes

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