Dog's Life: Wearable Activity Recognition for Dogs

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ABSTRACT
Health and well-being of dogs, either domesticated pets or service animals, are major concerns that are taken seriously for ethical, emotional, and financial reasons. Welfare assessments in dogs rely on objective observations of both frequency and variability of individual behaviour traits, which is often difficult to obtain in a dog's everyday life. In this paper we have identified a set of activities, which are linked to behaviour traits that are relevant for a dog's wellbeing. We developed a collar-worn accelerometry platform that records dog behaviours in naturalistic environments. A statistical classification framework is used for recognising dog activities. In an experimental evaluation we analysed the naturalistic behaviour of 18 dogs and were able to recognise a total of 17 different activities with approximately 70% classification accuracy. The presented system is the first of its kind that allows for robust and detailed analysis of dog activities in naturalistic environments.

Author Keywords
activity recognition, wearable computing, dog, animal wellbeing

ACM Classification Keywords
H.1.2 User/Machine Systems I.5 Pattern Recognition: J.4 Social and Behavioral Sciences

INTRODUCTION
Humans and dogs have lived together in close proximity for thousands of years [3], which has led to strong emotional and social bonds [15]. By far the largest number of dogs are kept as domesticated pets. For example, in the UK alone an estimated 31 percent of households own a dog, totalling to approx. 10.5 million animals [10]. Pet dogs often fulfil the role of companions or even friends [9]. Apart from this, dogs are widely employed as service animals to perform tasks that are deemed too dangerous, difficult or arduous for humans. Examples include dogs for the blind, search and rescue animals for emergency management, sniffer dogs for narcotics and explosives, and security dogs for policing.

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In both service and domestic dogs, the animal's health and well-being are major concerns that are taken seriously for ethical, emotional, and financial reasons. A common definition of animal welfare was laid down in 1979 by the British Farm Animal Welfare Council (FAWC) and encompasses 5 freedoms:*i)* hunger and thirst; *ii)* discomfort; *iii)* pain, injury, and disease; *iv)* fear and distress; and *v)* freedom to express normal behaviour. Whereas the former three have been well researched by veterinarians through direct measurements and observations, the latter are difficult to assess.

Objective observations of both frequency and variability of behaviour traits are key to welfare assessments in dogs where common practice is currently based around manual observational studies and questionnaires [14, 17]. The difficulties these present with regard to logistics as well as upscaling to larger populations are widely accepted as a barrier to gaining behavioural insights. For example, it is difficult to closely monitor dogs in natural outdoor environments or buildings with multiple rooms for long periods of time. However, this is a common situation for many animals to encounter and the majority of domestic dogs spend long periods of time at home alone. In addition, longitudinal measurements are particularly difficult as the frequency of some behaviours (e.g., eating) is difficult to quantitatively report manually.

With a view on assessing animal welfare there is a strong desire to automate detailed behaviour analysis for dogs. However, surprisingly little work has been done so far focusing on in-depth analysis of specific, assessment relevant behaviour traits that go beyond monitoring the general physical activities of dogs. Existing approaches (e.g., [11]) focus on logging overall activity patterns and related energy expenditure of the animals. While this allows for high-level analysis, it is not suitable for detailed assessment of specific behaviours and tracking of changes therein, as is desired by both vets and concerned dog owners.

We present an automatic behaviour assessment system for dogs based on a collar-worn accelerometer platform, and data analysis techniques that recognise typical dog activities. For real-world applications the system is capable of recording data for up to 30 days, and is waterproofed to enable use in rough working environments. We evaluate the system based on the analysis of 16 behaviour traits in 18 dogs, incorporating 13 breeds of various sizes, ages and of both sexes. Our analysis system successfully replicates manual assessments based on hand annotated video ground truth, which demonstrates the applicability of automated dog behaviour analysis for realistic use cases.

Behaviour (type)	Definition and Movement Characteristics (potential triggers)
Barking (A)	Vocalisation of loud sounds. Head is often elevated and thrown forwards at the moment of the bark. Often in bouts of multiple barks.(E,D)
Chewing (A)	Object in mouth of the dog. Typical chew motions corresponds to the lower mandibular moving rhythmically. Excludes ***Eating***.(E)
Digging (A)	Front paws move in conjunction with each other bimanually (consecutively or concurrently). At least one full motion circle required.(E)
Drinking (A)	Series of movements where the dog's tongue touches the liquid up to the swallow. A dog may often stop in between drinking to breathe. The head performs a bobbing motion. (E,D)
Eating(A)	Dog swallows the item it has in its mouth. Results in sequence of characteristic movements of the mandibular.(E,D)
Excreting(A)	When a dog excretes it will maintain a squatting position. Some dogs may take a few steps when defecating but their bodies are still held in a rigid position. (E,D)
Jumping (A)	Movements between the moment the paws (all four) leave the floor until they are back in contact with the ground.(E,I)
Laying (P)	Movements between the moment the hock and pastern are in contact with the floor and remain there for more than 1 second, until either the hocks or pasterns are no longer in contact. A dog may also lay on its side or on its back with its legs in the air.(E,I,D)
Pawing(A)	Front paws working independently of each other. A pawing action corresponds to repeated backwards pulls towards the dog's belly and hind legs of a single paw. (E,I)
Running (A)	Incorporates gaits referred to as *galopping* & *trotting* [5] resulting in forwards motion of the dog.(E,I,D)
Shaking(A)	Twisting motion starting form front of the dog's head and continuing along the whole body down to the tail.(E)
Shivering(A)	Muscles around the core of the dog shake in small vigorous movements. (E,D)
Sniffing (A)	Nose angled downwards and in close proximity to the floor. Often the head will make sharp side to side movements. Can be done while the dog is in motion or stationary.(E,D)
Sitting(P)	Movements between the moment the rump makes contact with the floor and remains there for more than 1 second, until the moment the rump leaves floor. In contrast to ***Laying*** the belly must not touch the ground.(E,I)
Urinating (A)	A male dog will often raise one of his rear legs in order to ensure that urine is sprayed in a forward direction. Bitches on the other hand will often squat down so that the urine is sprayed onto the floor between their rear legs. (E,D)
Walking(A)	Gait defined by [5] resulting in forward motion of the dog.(E,I,D)

Table 1. Definitions of typical dog behaviours as they are analysed by the automatic recognition system. Types: (A) – Action; (P) – Pose. Potential triggers offer an explanation for deviation in typical behaviour: (E) –Environmental (defined as manually controllable stimuli); (I) – Injury (defined as a recoverable state affecting animals mobility); (D) – Disease (defined as a semi-permenant state that could affect animal psychology or physiology).

DOG BEHAVIOUR

The literature on dog behaviour and well-being draws strong correlations on combinations of body movements to specific moods, intentions or desires of the animal, which are grouped as *communicative behaviours* [4, 8]. Such behaviours are composed of body movements that make up a complex body language the dog uses —often exclusively— to communicate with humans. The majority of such body language is deeply rooted in phylogeny of the genus. For example, when acting aggressively, a dog will often stand in a stiffened pose with its tail straight out, bearing its teeth while snarling or growling. This behaviour is designed to portray the dog in an intimidating pose such that an aggressor will be discouraged away from physical confrontation, thus preventing possible injury.

Dogs can also engage in what is termed *response behaviours* [6, 8]. These types of behaviours often only last short periods of time and are in response to environmental or stimulus based influences. An example of an environmental based response behaviour is shaking after a period of swimming. Response behaviours are not generally linked to dog-human interactions but are often used by vets as symptomatic indicators of injury or disease. For example, in the case of a fractured bone, a dog may spend extended periods of time lying because it is painful to walk.

In the same way humans present mal-state with abnormal behaviour, animal scientists have also linked certain behaviours as key indicators of disease and pain. Very often in the case of a disease such as arthritis that impairs mobility, the gradual initial stages of onset go un-noticed by owners. Such oversight can mean the animal goes untreated and is thus subjected to severe amounts of pain.

Table 1 gives a list of behaviours and potential triggers that are key in interpreting sudden or trending changes thereof.

AUTOMATIC ANALYSIS OF DOG ACTIVITIES USING A WEARABLE SENSING SYSTEM

Monitoring and tracking the health and well-being of dogs requires the analysis of the broad range of their everyday activities (Table 1). Since most of a dog's activities are linked to substantial physical movements, our automatic analysis system is therefore based on a worn accelerometry sensing platform. For almost all of a dog's activities its head plays an important role, either for directly performing the particular activities (e.g., barking, chewing, drinking), or for balancing full body movements (e.g., walking, running, shaking). It is for these reasons, as well as practical considerations such as comfort and minimal obstruction to the dogs activities, that the collar was chosen as the best site for the sensor.

Sensing Platform

The platform chosen for recording dog activities is an AX3 logging accelerometer manufactured by Axivity [2]. It contains a tri-axial MEMS accelerometer coupled to a PIC24 micro controller. The accelerometer can be sampled at a range of frequencies between $2.5 - 3,200$Hz and we chose a sampling rate of 30Hz in order to record detailed movement information. The samples from the accelerometer are timestamped to an accuracy of 20ppm and stored onto an inbuilt 4Gb NAND flash memory chip. With our chosen sampling rate the AX3 is capable of providing continuous data capture for a period of 14 days, which is sufficient for longer-term field studies. The sensor is housed in a tough polycarbonate casing which is hermetically sealed to an IP68 level of waterproofing (1.5m for a period of $1:30$ minutes) as well as carrying the CE safety mark certification. For sensor configuration and recharging, as well as for data download the platform contains a microUSB port in the side of the housing. Figure 1 illustrates the sensing platform.

Data Analysis

Working with animals carries specific challenges. For example, subjects are rarely cooperative and adherence to a strict activity protocol is impossible. In the case of activity recognition in dogs the former could result in the animal disturbing the sensor placement (e.g., excessive scratching will result in unwanted collar rotations), whereas the latter can result in unusual, idiosyncratic activities that have not been specified in

Figure 1. Collar based sensor platform used for activity recognition.

advance. The main requirement for an automatic analysis system is thus its robust and reliable operation, which supersedes the desire of high accuracy recognition of unusual activities.

The collar-worn sensing platform records a continuous stream of tri-axial accelerometer data. Focusing on aforementioned robustness, our analysis procedure utilises a segmentation-free analysis approach based on a sliding window procedure for frame extraction, PCA-based feature extraction, and an instance-based learning classification backend. All analysis is based on separate processing of small analysis windows that consist of 1s of consecutive accelerometry samples. Subsequent frames overlap by 50%, which is in line with the state-of-the-art in sliding window based activity recognition [13]. For normalisation of the raw sensor data we estimate their empirical cumulative density function (ECDF) and convolute input date with the inverse of the ECDF [7]. Keeping to the procedure described in [12] we further reduce the dimensionality of the features by projecting them onto the first 30 principal components (retaining more than 95% variance). The label for each frame is estimated by majority vote based on the ground truth annotation. However, frames where the majority label constitutes less than 75% of the frame width are withheld from training. This is done to alleviate some of the inconsistencies in annotation that result from ambiguous dog behaviour.

Finally, feature vectors extracted for every frame are fed into the classification backend, namely a k-Nearest Neighbour classifier (with $k = 1$), which is trained in a 10-fold cross validation and effectively discriminates between the 16 dog activities specified in Table 1 and one rejection class.

EXPERIMENTS

The overarching goal of our research is the development of an automatic activity monitor for dogs that provides insights into the temporal distribution of a predefined set of animal's behaviours. Such detailed information is invaluable for assessing a dog's health and well-being.

In order to evaluate the effectiveness of our system we conducted a case study in which we gave the recording platform to a number of dog-owners. We asked the participants to attach the sensor-equipped collar to their dog and record their activities in everyday situations. The owners of the dogs also wore a mobile camera to videotape the recorded activities. The resulting video footage was then used for ground truth annotation, which forms the foundation for our recognition evaluation. All dog owners gave their consent to participate in this study and to use their dog's data for our developments. No animals were harmed while conducting this study, which was conducted in full compliance with the "Animals (Scientific Procedures) Act 1986 (ASPA)" regulations of the UK's home office [1]. The techniques and protocols used in the study were approved by a University ethics committee.

Breed	#♀/ #♂	KC Size Class
Mongrel	1/1	na[1]
Miniature Jack Russell	0/1	S
Dachshund	0/1	S
Cocker Spaniel	0/2	M
English Springer Spaniel	0/1	M
Border Collie	0/1	M
Bulldog	1/0	M
Dalmatian	0/1	L
Labrador	1/1	L
Great Dane	1/2	L
Siberian Husky	1/0	L
Hungarian Vizsla	1/0	L
Weimaraner	0/1	L
total: 13	6/12	S:2; M: 4; L: 6

Table 2. Overview of the dogs participating in the experiment.

Dataset

The dogs used in our case study are listed in Table 2. They were chosen so that the dataset covered a wide range of ages, weights, and breeds, as well as both sexes. Each data collection exercise started with the recording platform being configured and attached to the particular dog's existing collar. The dogs were then filmed wearing the collar in both indoor and outdoor settings. For the majority of the recording time the dogs were left to behave how they liked and incidental instances of activities were captured. However, for a few animals it was necessary to make interactions that stimulated them to perform some of the activities in 1 (for example ball throwing was used to instigate a bout of running and encouragement to swim was used to instigate shaking). At the end of every data capture session, which lasted between $20-40$ mins for each dog, the recording device was removed and shaken in front of the camera. This action was subsequently used to synchronise the video and accelerometer data.

The data captured was hand annotated (by one expert) against video footage. Based on the definition of dog activities as summarised in Table 1 we gave annotators specific and detailed instructions about how to code the activities of the animals. In addition to the specification of the particular activities these guidelines also included precise instructions about coding start and stop points of particular behaviours. Using these instructions we ensured a reliable and objective ground truth annotation of the recorded dataset.

Results

After frames are extracted from the recorded data streams and labelled according to the ground truth annotation we form 10 stratified folds that are used to both extract features and train the KNN classifier in a cross validation procedure. This results in an overall recognition accuracy of 68.6%. Most of the confusion occurs between the rejection class and *walking*, as can clearly be seen in the confusion matrix (see Figure 2). This is largely due to the inaccurate annotation, as the transition between these two activities is not well defined. Other

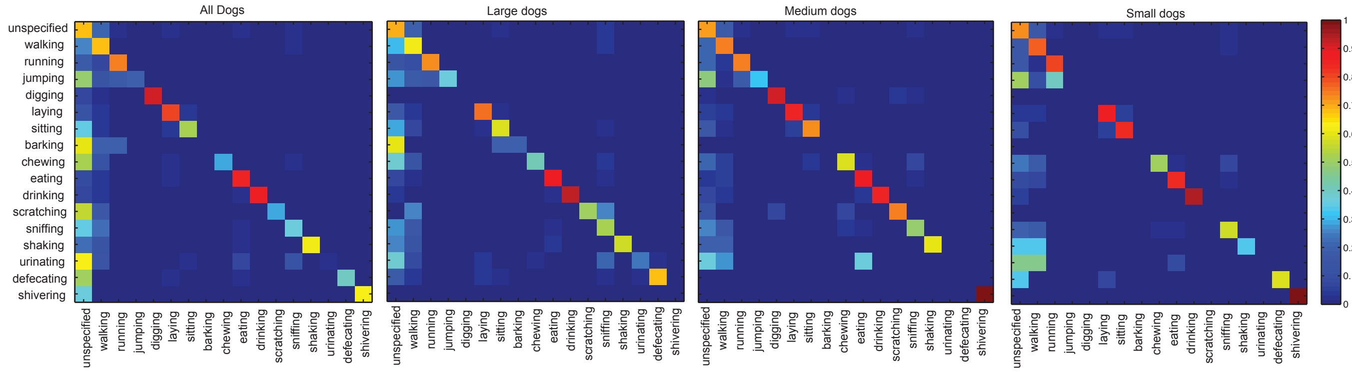

Figure 2. Confusion matrices illustrating classification performance. From left to right: i) all dogs, ii) large dogs, iii) medium dogs and iv) small dogs (according to Kennel Club sizing criteria).

activities can be differentiated at surprising reliability, such as *eating* and *drinking*.

Intuitively, characteristic patterns of the different activities of a dog are heavily influenced by its shoulder height. As an example, consider a very small dog like a Jack Russell, whose modes of transport differ significantly from a Labrador. In order to investigate whether results improve if dogs are grouped according to size, we conducted an experiment with three groups of dogs, classified according to the Kennel Club criteria [16]. Confusion matrices are illustrated in Fig. 2. The results improve significantly, particularly for small dogs, where modes of transport along with other activities such as digging can be differentiated much more effectively.

It is also anticipated that the results could further be improved through the addition of a multi-variate window size. For example features such as barking and jumping are temporally short in nature and are not well segmented using the same window as sitting or lying.

SUMMARY

Health and wellbeing are of major concern for both domesticated pet dogs and service canines. We have presented a collar-worn activity monitor and a classification system that is capable of recognising 17 dog activities that were expertly identified as being relevant for dog behaviour traits. In a large scale experimental evaluation we have demonstrated that our approach can successfully recognise the aforementioned activities with a reliability of approximately 70%.

The system is the first of its kind that allows for behaviour monitoring of dogs in naturalistic settings. This is important especially for monitoring the welfare of animals that spend a significant time on their own where the owners typically do not have detailed information about their dog's everyday activities and wellbeing. Furthermore, our system could be used for objective assessments of injury recovery and healthiness in service dogs, which has substantial economical impact.

In the future we will explore coupling the core elements demonstrated herein with a fully-automated wireless data transfer and a meaningful graphical visualisation. Such a system has the potential to deliver real time web-based results which opens up the design space for a range of applications such as early warning systems or progress tracking.

[1]No KC classification for mixture breeds.

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