WagTag™: A Dog Collar Accessory for Monitoring Canine Activity Levels

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Abstract

Technological advancements are leading to the emergence of wearable computing devices as a major consumer category. Several companies have developed, or are developing, wearable accessories to monitor human activity. But the health and wellness applications associated with these accessories can also benefit non-humans, and wearable computing accessories with such apps are now emerging for the pet market. In this paper we describe WagTag™, an accessory that can be attached to a dog collar to track a dog's activities and the intensity of these activities. The activity information is visually displayed on the device, while more detailed information can be uploaded to a computer via a Bluetooth connection. We describe key design issues and goals associated with the development of this device, especially with respect to aesthetics, durability, and functionality, and also describe WagTag's prototype activity recognition models.

Author Keywords

Activity recognition; mobile health; ubiquitous computing; data mining; sensors; wearable computing.

ACM Classification Keywords

J.3. Computer Applications: Life and Medical Sciences-Health.

Motivation for WagTag™

Enabling technology: low cost sensors, low power processors, cheap memory, Bluetooth, smartphones for BT connection

Experience with similar technology for humans: FitBit® and Jawbone Up are currently available and in the future Apple and Google will likely come out with watches. All of these should be able to monitor activities.

Market: 78 million pet dogs in U.S. and their owners spent $53B in 2012 [6]. Trend to humanize pets and dogs are often treated as well as humans (e.g., gourmet food, pet clothes, etc.)

Need: 54% of dogs and cats are overweight or obese [7]. Dogs are largely dependent on their owner.

Introduction

The development of very low cost sensors and low power mobile devices, along with the rise of innovative mobile applications, has led to the emergence of wearable computing. Wearable accessories are at the forefront of this new industry and major corporations are now actively working to bring new accessories to market, or to refine the ones already on the market. The corporations involved include computing giants such as Apple and Google, startups such as Fitbit and Jawbone, and apparel makers such as Nike. All of these accessories are likely to track human activity 24 hours a day as either their primary function or as a secondary function. Various mobile health, or mHealth, applications will be built on top of this technology, and these applications can ultimately help improve the health of the wearers. Applications associated with these devices can help assess whether people are sufficiently active to ensure proper health, and have the potential to promote changes in behavior and a more active lifestyle.

There are several reasons to believe that there is a strong market for devices to monitor the activity levels of pets. In the United States 53% of all dogs are overweight or obese, with 24.4M (31.2%) being overweight and 16.7M (21.4%) being obese [2]. Pet obesity is a major issue as it can reduce the life expectancy of a pet by up to 2.5 years and lead to other serious diseases [2]. Undoubtedly much of this obesity is due to inactivity, as is the case for humans.

Pet owners also seem willing to spend tremendous amounts of money on their pets. Americans alone spent $53B on their pets in 2012 [5]—more than on video games ($25B), movies ($18.6B) and digital music ($5.2B) combined. There has also been tremendous growth in pet products and supplies due to the growing number of pet owners and pets. Approximately 62% of all US households own a pet; of these approximately 47 million are dog owners who collectively own 78 million dogs [5]. Over the last 10 years there also has been a trend to humanize pets, and this suggests that pet owners will be willing to purchase devices similar to ones designed for humans. Companies like Paul Mitchell, Omaha Steaks, Old Navy and Harley Davidson, known for human products, are moving to provide premium products for dogs and cats. You can now find pet products ranging from dog shampoo, pet attire, and name-brand toys, to gourmet treats and food.

Dog owners are ultimately responsible for regulating their dog's caloric intake and ensuring sufficient physical activity. However, no systems exist to help dog owners quantify the physical activity their dog exerts. No mechanisms exist to consistently track physical activity during walks or during the day when the owner is not home. To address this need we introduce the WagTag™, an accessory that attaches to a dog's collar. This device will track a dog's activity levels and let the dog owner know whether the dog is sufficiently active. The device uses a tri-axial accelerometer to monitor the motion (i.e., the acceleration) of the dog, and the accelerometer data are fed into an activity-level recognition model that executes on the device. This model identifies the level of activity that the dog is performing and updates summary statistics on the device. Activity information is then displayed on the WagTag, including an indication of whether the dog is sufficiently active. More detailed information can be uploaded to a smartphone app via a Bluetooth connection. The WagTag™ is currently in the prototype stage.

Related Pet Monitors and Trackers

In recent months, several devices have either been announced or entered the market to help track and manage pet activity. We very briefly mention three of the most notable products, which all have different designs and use cases.

TAGG (www.pettracker.com) is a pet tracking device owned by wireless giant Qualcomm. The primary purpose of this device is to track lost dogs, but the device was recently augmented to monitor pet health via activity summaries. The device has a GPS chip and requires a $7.99 monthly fee. Pet owners can track information via an accompanying app. A second device, FitBark (www.fitbark.com), is a bone shaped activity tracker that attaches to a dog's collar. Fitbark has created a proprietary activity score that measures the dog's health and weekly activity. As with TAGG, the primary interface for a pet owner is through an iPhone app. The newest entry into the rapidly growing market is Whistle (www.whistle.com). This on-collar device measures a dog's activity throughout the day. While functionally similar to Fitbark, the design is sleeker. However, an app is still the primary interface for pet owners to track information about their pet.

The rapidly growing market for pet activity monitoring devices indicates that there is a real demand for tools to address pet health. However, the current crop of devices do not incorporate a visual interface on the device and thus do not permit a pet owner to get immediate information on the status of their pet's health and activities without the need for a smartphone. As will be seen in the next section, WagTag™ addresses this issue by building a visual interface into the device.

Overview of the WagTag™

The WagTag™ is a dog collar accessory that contains a tri-axial accelerometer, a computer processor, and a memory card. The tri-axial accelerometer measures acceleration in all three spatial dimensions and is similar to the accelerometers that are incorporated into smartphones. The accelerometer is sampled at 20Hz and the results are stored on the WagTag's memory card. The device is designed to operate for several days at a time without recharging.

In order to monitor the dog's activities, WagTag™ classifies all activities into one of the three following activity levels: minimal activity, walking activity, or running activity. These classifications are made continuously and are used to generate the higher level information that is communicated to the dog owner. The three activity levels are defined as follows:

- <u>Minimal activity</u>: the dog is not moving, is lying down, or is otherwise inactive.
- <u>Walking activity</u>: the dog is either walking slowly or briskly.
- <u>Running activity</u>: the dog is running at a good pace. This high activity phase may include fetching and catching.

In our current implementation, the activity level classifications are issued every 10 seconds. The activity level classification is performed by our classification model, which is described shortly. The activity information will be displayed visually on the WagTag™, while more detailed information will be displayed on the WagTag's phone app. The overall execution flow of the WagTag™ is shown in Figure 1.

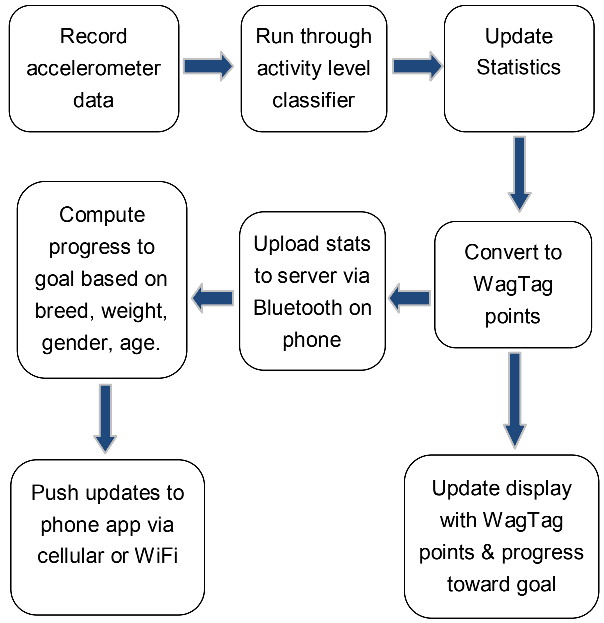

Figure 1: The execution flow for WagTag. Accelerometer data are continuously streamed to the activity classifier. This identifies the dog's current activity level, updates internal statistics, and converts these statistics to WagTag points, which represent the dog's overall activity status. This information is displayed on WagTag as well as on the WagTag phone app.

WagTag™ Design

Several design challenges were faced in creating a wearable computing device for dogs. Interestingly, many of the design issues are the same as for humans: the wearable device has to account for differences in clothing, fashion, and location of the wearable device based on ergonomic concerns. It should be noted that pets, especially dogs, are often viewed as a reflection of their owner. The WagTag™ design needs to be adaptable to wide variety of dogs and situations, so that it is suitable for both a police canine unit and a teenager's pet Labrador. Furthermore, there is a much greater size variance associated with dogs than with humans and this must be considered. WagTag™ also must be rugged, since dogs are not likely to alter their behavior because they might damage the device. WagTag™ has the additional requirement that it must be readable when the owner is at leash distance, or even slightly farther away.

To solve these challenges, several key decisions were made. Because a dog collar is often a strong reflection of the personality of the owner, we decided not to build a new collar, but rather to build a device that can be attached to existing collars. This decision required us to design a device that could attach securely to a variety of collar widths and thicknesses. But by not building a full collar, we had little room for electronics and the visual interface.

We addressed these issues by separating the battery from the electronics and placing the attachment method in between. By sandwiching the device around the collar we were able to nearly halve the visual footprint and perceived depth. Aesthetically the design was kept simple so that it would blend in with a wide variety of collar designs and styles. The visual interface was also designed to be simple, providing general activity information from a distance and more detailed information when close up. A mobile and web app accompany the device to provide detailed information.

We believe that when compared to other devices on the market, we have a more appropriate looking device and one that better satisfies the needs of the dog owners.

For example, Fitbark, which is bone-shaped, provides a "traditional pet" aesthetic, but does not really consider the unique context in which the product exists. A **critical finding** in our product research was that dogs are generally cared for by multiple caregivers and thus multiple people need to be able to interact with our device (and not all may have smartphones). We knew that at least a base level "current status" aspect was needed. Whistle, while exceedingly slick in appearance, lacks this basic ability to quickly indicate the real time status of the dog by tying the entire interface to the user's iPhone.

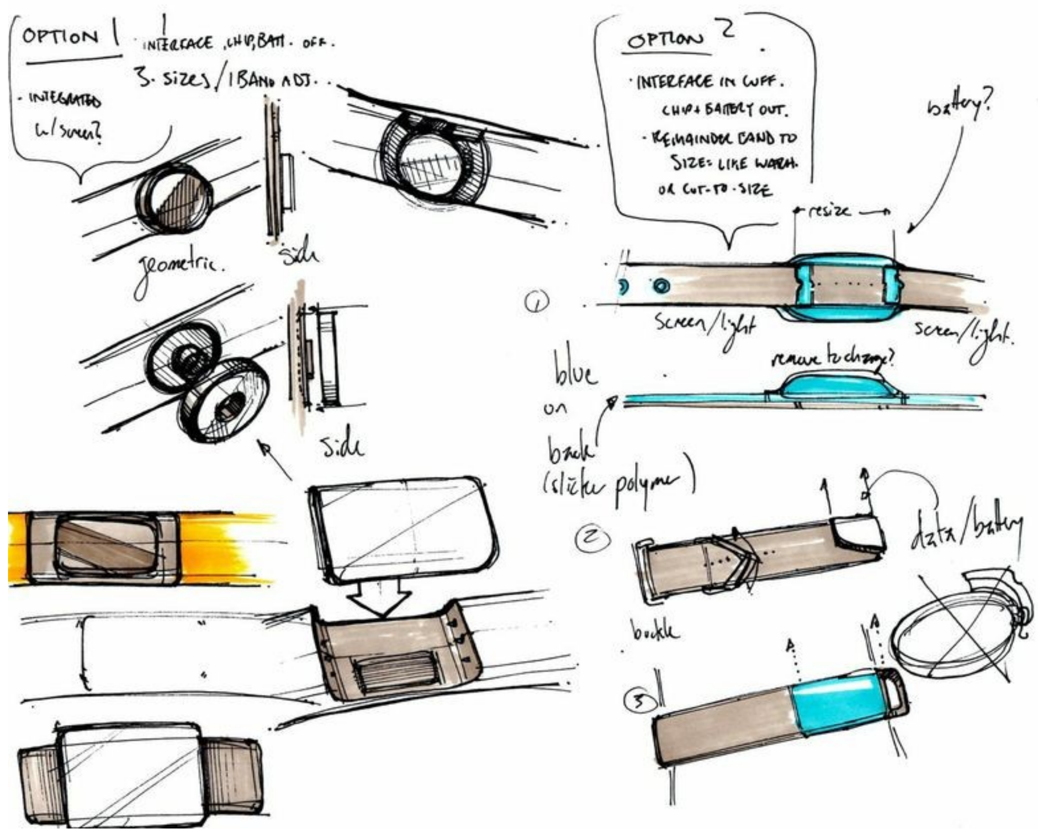

Figure 2: Early design sketches of the WagTag™ exploring different design options.

The WagTag™ has to be rugged and our main strategy in this regard was to reduce the device's profile—and hence risk of getting damaged. This approach also dovetails with our goal of keeping the design simple so that it would easily blend in with a variety of dog collars. Because our device sandwiches around the dog collar, half of our device is protected by the collar itself. We further minimize the impact capability by chamfering the outer edges and applying a dense rubber protective edge. Also, because our device is split into two components with a semi-flexible hinge between, we can maximize the casing protection for the two components. The flexible hinge in between, combined with our unique clamping system, also assures that the device is only removable by the owner. The low-profile design of our device differs from the design of products like Fitbark and Tagg, and to a lesser extent, Whistle. Those devices tend to show off their device more and in doing so subject the device to increased leverage and impact forces and, in particular, provide the dog with something substantial to scratch against.

Through the design process we have successfully created a device for dogs that not only works on a full range of collars, minimizes the risk of being damaged due to the low profile, but is also aesthetically pleasing and desirable for the dog owner. Some of the design sketches are shown in Figure 2, but the final design is not provided since the device is not yet on the market.

Activity Level Classification

One component of the WagTag™ is the activity level classification model. This model maps the accelerometer data to one of the three activity levels that were described earlier. The model is generated using standard machine learning methods (e.g., decision trees algorithms) and then is implemented in software on the WagTag™.

The scheme that we use to generate the model performs quite well in our work on human activity recognition [4], but our current results for recognizing the dog activity levels are not particularly impressive and must be improved before the WagTag™ is released. As will be described shortly, the results for this first prototype model suffer due to a lack of training data, a very limited number of dogs in the training set, and likely errors in assigning the class labels. We expect that all of these causes can be addressed in the near future and that this will lead to much better classification performance.

The Dog Activity Data

Classification induction algorithms require labeled training data to construct a model and to evaluate the accuracy of the resulting model. Our data came from 7 dogs that were monitored as they performed various activities, so that the appropriate activity-level labels could be appended to the accelerometer data. In this initial round of data collection the dogs were not necessarily performing the labeled activity continuously (e.g., may have walked for a short while during running) and hence we expect that the class labels are sometimes not properly assigned. We will correct this in future data collections.

The dogs were of different ages, weights, genders, and breeds, and these characteristics were recorded so that we could determine if such information can improve the accuracy of the models. However, with only 7 dogs in our sample, we did not have a sufficiently large sample to assess the impact of these characteristics. For example, the current sample includes 4 Labrador Retrievers, 2 Golden Doodles, and 1 Boxer, which means we only had a realistic chance to learn breed-specific patterns for the Labrador Retrievers. A much larger sample of dogs would be useful for this type of learning and very possibly would boost the performance of the models. We are currently in the process of obtaining a second, much larger, round of training data from a larger panel of dogs. It will be interesting to see which traits can be utilized to improve the performance of the models.

Classifier Induction

WagTag™ relies heavily on a classifier to map the accelerometer data into one of the three activity levels. This task is very similar to the task of human activity recognition [1], where accelerometer data (or other data) are used to identify the specific activity the human is performing. In prior work, several of this paper's authors have built and evaluated human activity recognition models using smartphone accelerometers [4,6]. We were able to adapt this prior work, with virtually no changes, to the task of identifying the three activity levels from the accelerometer data. We simply provided different training data with different activity labels. We only outline the process of generating the activity level classifiers here and the reader should refer to the prior papers [4,6] for additional details.

Classifier induction algorithms learn to classify examples, or objects. In our case we want to learn to classify accelerometer data as being associated with a specific activity level. Because the classifier induction algorithms that we employ do not operate directly on time-series data, we must first transform the raw accelerometer data into examples. We do this by taking 10-second segments of accelerometer data and from this generate 43 descriptive features [4,6]. We then use a number of classification algorithms from the WEKA data mining suite [7] to build the models, including Random Forest, Instance-based learning (IBk), and Neural Networks.

We built two types of models: universal models and personal models [6]. The universal models are built from training data that do not include the dog whose activities are to be classified, while personal models are built only using data from the dog whose activities are to be classified. The universal models are more readily usable because they can be used on a dog without requiring labeled training data for that dog, while personal models require a training phase for each new dog (which would require the owner to do some work). We mainly report the performance for personalized models because we view this as an upper bound on the performance for the universal models. We also believe that once we have more training data we can obtain many of the benefits of the personal models by utilizing the characteristics of the dog (e.g., breed, weight, etc.). We expect that these characteristics will be very useful because it seems reasonable that the size of a dog would impact our ability to determine, based on accelerometer values, whether the dog is walking or running.

Preliminary Results

The classification models must be evaluated with respect to some evaluation metric. One metric that we use is classification accuracy, which represents the fraction of the activity-level predictions that are correct. But our ultimate goal is not to provide high classification accuracy, but to accurately *quantify* [3] the total amount of time that a dog spends at each

(a) Personal Model Results			
Dog	**Walk**	**Run**	**Minimal**
1	**9.2**	**2.0**	**5.3**
	8.8	1.7	6.0
2	**4.3**	**0.0**	**1.2**
	4.5	0.0	1.0
3	**4.5**	**3.2**	**2.8**
	4.0	3.7	2.8
4	**9.5**	**0.0**	**0.0**
	9.5	0.0	0.0
5	**2.2**	**1.8**	**3.5**
	2.5	1.3	3.7
6	**2.3**	**4.2**	**3.2**
	2.3	4.5	2.8
7	**1.3**	**1.3**	**2.5**
	1.5	1.2	2.5

(b) Universal Model Results			
Dog	**Walk**	**Run**	**Minimal**
1	**9.2**	**2.0**	**5.3**
	10.5	1.0	5.0
2	**4.3**	**0.0**	**1.2**
	2.2	1.2	2.2
3	**4.5**	**3.2**	**2.8**
	8.3	1.2	1.0
4	**9.5**	**0.0**	**0.0**
	3.2	5.7	0.7
5	**2.2**	**1.8**	**3.5**
	2.8	1.3	3.3
6	**2.3**	**4.2**	**3.2**
	6.3	2.2	1.2
7	**1.3**	**1.3**	**2.5**
	2.3	0.0	2.8

Table 1: Quantification results for personal and universal models. Values are of *actual* minutes per dog per activity (in bold) and (below that) *predicted* number of minutes.

activity level. We compute quantification accuracy for each of the 3 activity levels and present the results in this section. Given that *A* is the actual known quantity (i.e., duration) of the specified activity level and *P* is the predicted/estimated quantity of that activity level, quantification accuracy is given by Equation 1 below. As an example, a quantification accuracy of 0.92 means that the estimated quantity of the activity level differed (either over or under) from the actual amount by 8%.

$$\text{Quantification Accuracy} = 1 - \frac{|A - P|}{A} \qquad [1]$$

Results for Personal Models

The personal models generate extremely good results. The overall classification accuracy, when averaged over all dogs, is 85%. The quantification accuracy, which is even more important, is 0.93 for the walking activity level, 0.84 for the running activity level, and 0.93 for the minimal activity level. The detailed quantification results are provided in Table 1a. We see that the estimated number of minutes very closely mimics the actual number of minutes. Many of the classification errors must cancel out since quantification accuracy is significantly higher than classification accuracy for two of the three activities. It should be pointed out that for Dog 4 we only had data for one activity and in this case it is not surprising that the predictions perform well.

Results for Universal Models

The results for the universal models are not nearly as good as for the personal models. The overall classification accuracy is 52% and the detailed quantification results are displayed in Table 1b. Certain dogs, like Dog 1 and Dog 5, generate fairly accurate quantification predictions, but Dog 4 yields poor results in that the walking activity is greatly under-estimated while the running activity is greatly over-estimated. Most of the problems result from confusion between the walking and running activity levels—the estimates for the minimal activity level are fairly accurate. This confusion may be due to the fact that different sized dogs or different breeds appear to walk or run very differently. This confusion may be addressed when we receive additional training data from a much broader selection of dogs. The problem can also be due to a lack of consistency in the labeling of the training data with respect to what constitutes running versus walking, which we plan to correct this in our next round of data collection.

Conclusion

In this paper we described WagTag™, a device that can be attached to a dog collar to monitor the amount of time that a dog spends at different activity levels. The device includes an accelerometer, a processor, and memory and includes a visual interface so that activity information can be conveyed to the dog owner without the need for a smartphone or computer. The device relies on an activity-level recognition model, implemented in software on the device. Our preliminary models, built from a very small amount of training data from just seven dogs, perform very well when personalized for a particular dog but do not yet perform well without personalization.

Many improvements will be made to the WagTag™ as the product is refined. We expect some minor changes to the physical characteristics of the device as we gain more feedback as the device is tested. We also expect the universal activity recognition models to improve significantly as we obtain much more training data from a wider variety of dogs and utilize the characteristics of the dogs (e.g., breed, size). More information on the device will be posted *to* www.wagtag.com as it becomes available.

This paper brings up several interesting issues that relate to the wearability of smart accessories, which can promote productive discussion in the wearable computing community. A central issue regards the tradeoffs between aesthetics, functionality, and durability, and, in the context of this work, how existing pet activity recognition products score in each of these areas. It appears as if the design of some products does not consider durability (i.e., high profile devices that are subject to impact and scratching) and may also favor aesthetics over functionality by not providing a direct visual interface to the device. WagTag makes different—and we would argue superior—design decisions in how to handle these factors, although this is certainly subject to debate.

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