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Wireless Inertial Sensors for Monitoring Animal Behavior

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Abstract—**Wireless sensors were designed which are small and light enough to be worn by small animals such as rats. These sensors are used to record three axes acceleration data from animals during natural behavior in a cage. The behavior of the animal is further extracted from the recorded acceleration data using neural network based pattern recognition algorithms. Successful recognition of eating, grooming and standing are demonstrated using this approach. Finally another potential application of this research is demonstrated in behavioral neuroscience by showing correlations between action potentials recorded from the motor cortex of a rat and acceleration data.**

I. INTRODUCTION

MONITORING the behavior of animals in a laboratory setting is a topic of interest for a large number of researchers. Research using animal models plays a vital role in the development of new medicines and vaccines. However it is largely a manual process, so there are limitations on how often observations can be made, and how thoroughly these observations can be analyzed. Better monitoring could help improve the collection and analysis of data from animal studies and reduce the number of animals needed in such research. The work in this paper concentrates on monitoring rats but it can easily be generalized to other species.

Many systems have been proposed for the recognition of behavioral states in the rat. One commonly used technique is video surveillance which has the important advantage of being non-intrusive. However, most current approaches require overhead cameras or cameras facing the long side of the cage [1], [2]. Most vivariums have cages stacked in close proximity with only the short side of the cage facing the outside, and implementation of such technologies would require significant redesign of cages and the rooms in which they are placed. Moreover, many of these algorithms fare poorly when multiple animals are present in the same cage. Some other approaches developed include the use of piezo or pressure sensors on the floor of the cage and the use of Continuous-wave Doppler radar (CWDR) signals to discriminate animal behaviors [3]. Both technologies fare poorly in the presence of multiple animals in a cage which is the norm. Moreover it would be of great value if the system could monitor the activity as well as physiological quantities like temperature of the animal.

The last few years has seen an explosion in sensor networks research with the development of many different hardware and software platforms; see for example the proceedings of SenSys, 2003 – present. Concurrently, advances in Micro Electro Mechanical Systems (MEMS) technologies have enabled the development of packaged low power accelerometers and other inertial sensors. In recent years, significant effort has been expended into making wireless inertial sensors small enough to enable biological applications. For example, Hitachi has demonstrated a wristband sensor node which can record the motion and pulse of a person and transmit it wirelessly to a base station [4]. This device measures 6cm x 4cm and weighs 50grams. Researchers have attempted analysis of animal behavior using inertial sensors in the past but these have been restricted to large systems unsuitable for small animals and lacking wireless telemetry capabilities [5], [6]. Ideally, the sensor used for small animals such as rats or mice would be less than 1cm^3 in size and weigh less than 5grams. Wireless sensors at this size scale have also been demonstrated in recent years [7], [8]

As a first generation device, we have built a wireless accelerometer which is 3cm x 2.5cm in size and weighs 10grams. This sensor is small enough to be tested on rats. Three axes acceleration data has been recorded from rats and wirelessly transmitted to a base station using this system. This data can be used to record and measure the activity of the animal over time. Multiple animals and hence multiple transmitters in close proximity is not an issue so long as appropriate protocols are used for data transmission. Further, we demonstrate that various behaviors of the animal such as standing, eating and grooming can be extracted from this acceleration data using neural network based algorithms. Finally we demonstrate another potential application of this research in behavioral neuroscience by showing correlates between signals recorded from the motor cortex of a rat and acceleration data.

II. METHODS

A. Hardware

As a wireless frontend, a SmartMesh mote from Dust Networks which contains a Radio transceiver, a microcontroller, analog to digital converters etc. on a single

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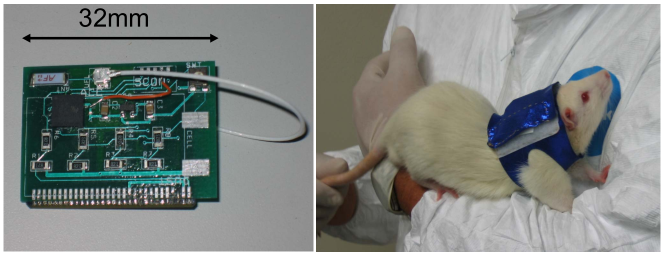

Figure 1: (a) The 32mm x 25mm wireless accelerometer prior to packaging (b) The wireless sensor being tested on adult rats.

board was used. This board controls the sampling of data from the sensors, providing accurate timestamps and transmission of data over the 2.4GHz frequency band. It uses frequency-hopping spread-spectrum communication for interference immunity and duty cycles components like the transceiver when not in use to extend battery life.

A sensor interface was developed as a separate board which could be attached to the SmartMesh mote. This sensor board contains a three axis accelerometer (MMA7260Q, Freescale Semiconductor), a chip antenna (Rainsun), a 150mAh rechargeable lithium polymer battery (Roomflight), voltage regulator, switch and passive components. The completed wireless sensor weighs 10.2grams and measures 32mm x 25mm and is shown in Figure 1(a).

The accelerometer can be sampled at 36samples/s using our current protocol. However this number can be increased in the future using modifications to the software. At this data rate, the transceiver uses approximately 600µA and the accelerometer approximately 500µA which gives the device a lifetime of over 5 days.

B. *Testing*

The sensor was tested on adult Sprague Dawley rats which weighed approximately 300grams and were 1 foot long. All animal procedures were approved by oversight committees at the University of California, Berkeley and were consistent with NIH and USDA regulations. The sensor was mounted using a specially designed vest or a rat jacket from Harvard Apparatus and is shown in Figure 1(b). This jacket is often used during behavioral training of rats and the rat comfortably moves around the cage with the sensor. It was also verified that multiple animals in a cage with sensors did not disturb each other's jackets. More long term testing is required to verify that the presence of the sensor does not significantly alter the behavior or stress level of the animal.

The acceleration sensors measure both accelerations related to movements of the animal and gravitational acceleration (g). Figure 2 shows three axes acceleration data collected from a rat freely moving in a cage. Typically one axis shows a mean of 1g due to gravity and the other two axes show around 0g as we would expect. During the period of this recording, the rat was initially moving around the cage and then fell asleep and that is clearly seen from the acceleration data. Hence the recorded acceleration data can be used to obtain some quantitative measure of 'activity' of the animal and also to monitor its sleeping patterns. Clinical

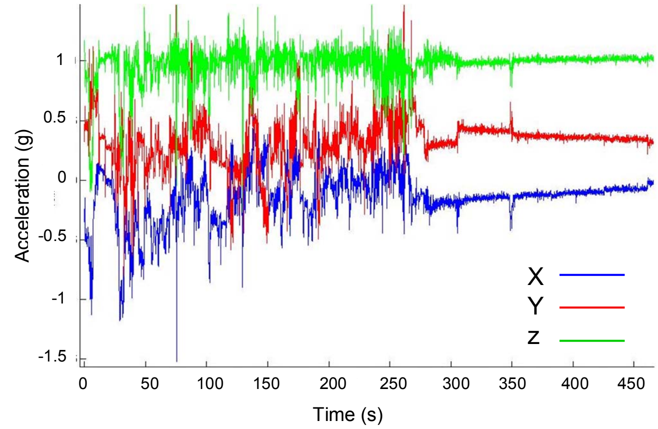

Figure 2: Three axes acceleration data as recorded from a rat moving freely in a cage show that the rat was initially active and then fell asleep.

relevance of these two metrics is expected to be high and needs to be studied over longer trials. We would also like to extract periods of relevant behaviors from this acceleration data and this is an interesting pattern recognition problem.

C. *Behavior Recognition*

The behaviors which we decided to categorize were standing, eating and grooming. Standing is when the animal stands on its rear legs, eating is when the animal eats a small piece of food and grooming is when the animal uses its forearms to clean itself. Grooming is a behavior of particular interest since rats groom themselves to keep themselves clean and tend not to do so when unhealthy [9]. Hence length of time spent grooming each day could be a good indicator of well being of the animal. These three behaviors were manually recorded in order to train the algorithms. Figure 4 shows three axes acceleration as recorded from a rat along with recordings of its behaviors.

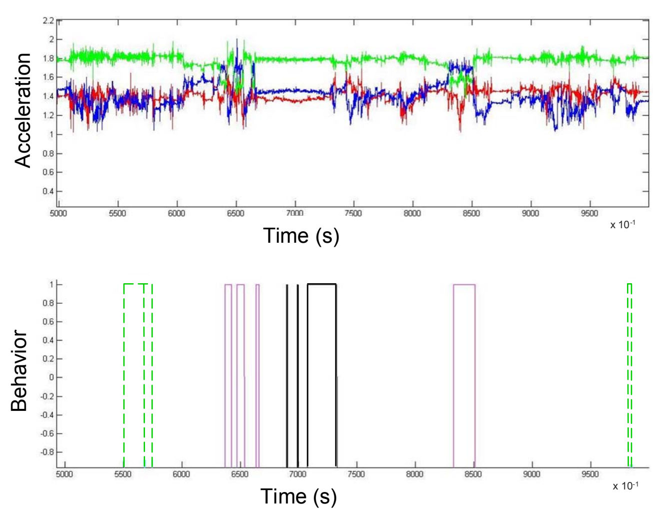

Figure 3: Behavior of the rat as recorded manually during recording of acceleration data.

The acceleration data used for behavior recognition was obtained using a wired version of the same accelerometer to aid in accurate time-stamping of data with respect to behavioral and neural data. 36 gauge wires attached to a multichannel commutator (Plexon Inc, Dallas Tx) were used to allow the animal free movement in the cage. The acceleration data was sampled at 20samples/sec and preprocessed depending on the behavior being detected. Eating and grooming performed best with data high-pass filtered at 2Hz while standing algorithms performed best using raw data.

To analyze the data and recognize patterns of behavior, we used a supervised learning algorithm. A 2 layer neural network with 5 hidden units was chosen for this purpose. Each unit performs the computation

$$y_i = \sigma\left(\sum_j W_{ij} x_j\right),$$

where y_i is the output of the unit, x_j are the inputs to the unit, W_{ij} are the weights assigned to individual inputs and σ is a nonlinear (sigmoidal) function.

It is essential to provide the neural network with information regarding the frequency content of the acceleration data. This can either be done by performing a sliding window Fourier transform on the data and feeding this as the input or by feeding data for the current time instant as well as 'n' previous time instants. The second approach showed better performance and hence was chosen. The recorded behavior serves as the desired answer for the neural network during the training period. The network was trained using a standard back-propagation algorithm. Other possible algorithms for this purpose include Independent component analysis (ICA), Support vector machines (SVM) and the K nearest neighbor algorithm. It is still an open question as to which algorithm is optimally suited to analyzing data from such inertial sensors [10].

III. Results

A. Behavior Recognition

Post processing involved low pass filtering and thresholding the neural network output and the results are shown in Figures 4 and 5. In both figures, the first part of the data was used to train the algorithm and the second part of the data was used to test the algorithm. In this case, the algorithm achieved 97% accuracy in recognition of periods of standing and 93% accuracy in periods of eating. This is a typical value of the performance of the algorithm over multiple trials. The performance in grooming is similar to that in eating.

The performance of the algorithm is worse if it is trained on data from one day and its performance tested on another day's data. One reason for this problem is that the sensor is mounted in a slightly different way each time it is taken off and put back on. This causes a rotation in space and 1g is distributed among the three axes in a different way. One method to reduce this problem is to mount the sensor in an identical fashion on the animal everyday or calibrate the sensor during characteristic movements. Another option is to use an inertial sensor which contains a 3 axes accelerometer and a 3 axes gyroscope, for e.g. the ADIS16350 from Analog Devices. However this comes with a major power penalty since it consumes 48mA and significantly reduces the lifetime of the device.

B. Applications in Behavioral Neuroscience

A potential application of this technology is to monitor the behavior of animals during experiments. Behavior recording of animals is typically performed in a test chamber with the animal performing tasks such as a forelimb reach for food or activating an infrared sensor within a nose poke. These methods have some inherent limitations since they tend to record only part of the behavior of the animal. For example,

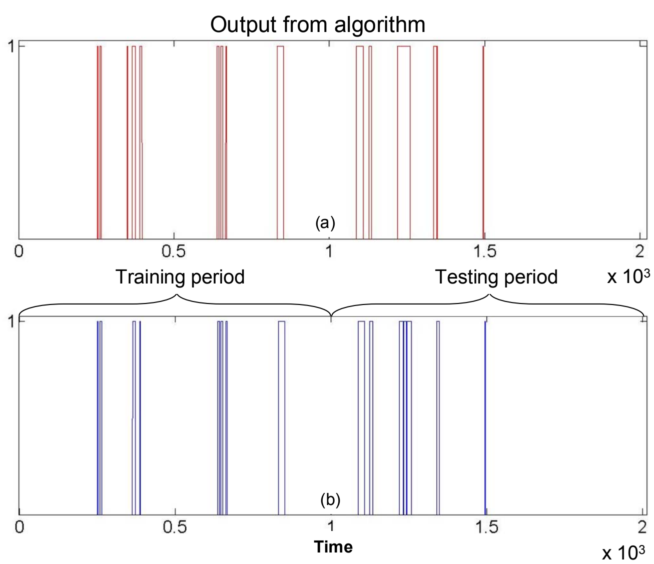

Figure 4 (a) Neural network recognition of standing
(b) Manually recorded periods of standing.

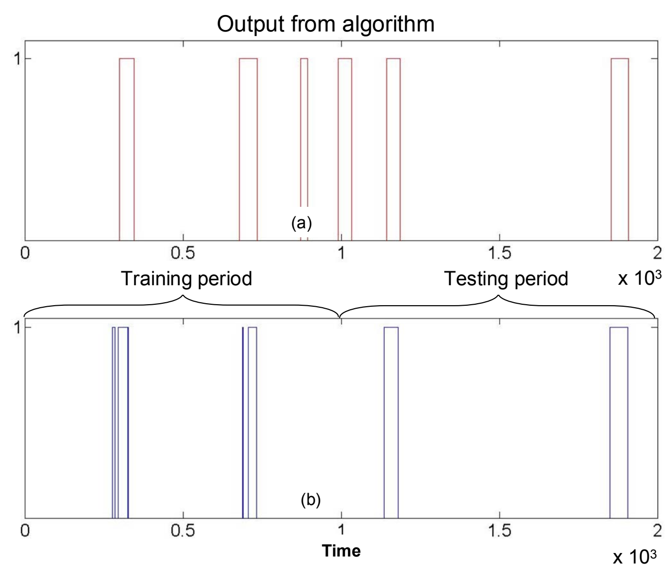

Figure 5: (a) Neural network recognition of eating
(b) Manually recorded periods of eating.

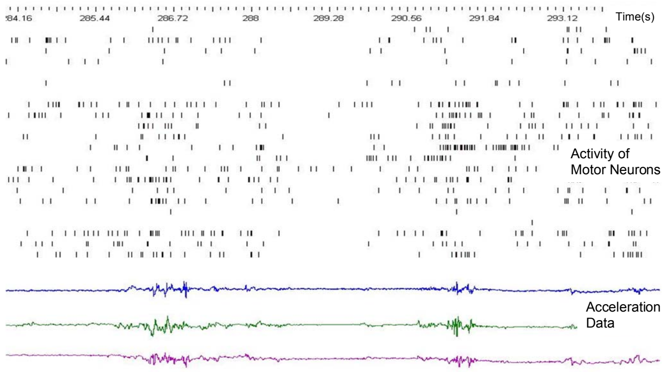

Figure 6: Action potentials of cells from the motor cortex of a rat are seen to be well correlated to acceleration values. Each row in the raster plot represents a cell and each vertical line represents an instant when the cell fired. The traces below show simultaneously recorded acceleration data.

it has been shown that reach-related activity in shoulder muscles and shoulder movement can precede attainment of the goal of the movement (attaining food) by 400 ms or more [11]. Such analysis is of particular importance for studies of motor areas of the brain, if it is desired to assign neural activity to the pre-motor and motor phases of the task. Researchers typically solve this problem by designing more complex tasks or by using other techniques such as subcutaneous Electromyogram (EMG) recordings [11] or frame by frame video monitoring to accurately measure the behavior of the animal. Our goal is to develop a non invasive rodent monitoring system to help control for rat behavior during the collection of electrophysiological data that avoids experimenter intervention and bias. Measuring the acceleration of the animal during the performance of a task or during free behavior provides us with such a system.

We are interested in studying the neural correlates of behavior. Neural signals were recorded from the somatosensory and motor cortices of rats using implanted electrodes and techniques similar to those presented in [12]. Figure 6 shows action potentials recorded from the motor cortex of a rat along with simultaneously recorded acceleration data. The rows above represent the firing of motor neurons in a rat and the traces below show the simultaneously recorded acceleration data. It is well known that neural activity in the motor cortex correlates well with overt movement. In the acceleration data, two periods when the rat was very active are visible and it can be seen that this correlates very well to the periods when the cells in the motor cortex were most active. Thus acceleration data can serve to provide information about the animal's behavior concurrent with recorded neural data.

IV. Discussion

Once a wireless sensor platform has been implemented, it is reasonably simple to add other sensors to this system. For example, one can add pulse sensors, temperature sensors etc which could be of great help to assess the health of the animal. By providing a vivarium-wide collection of continuous animal health measurements, this technology could aid in drug design and medical research as well as veterinary science and animal care in zoos and agriculture. Another application of this work is for the analysis of activity and behavior in humans.

V. Conclusion

Our work has demonstrated that wireless accelerometers are a viable means for monitoring overt behavior in rats. Overt behavior need not be limited to those we attempted to observe in this study nor is the application restricted to rats. In the future, we would like to develop smaller and lighter wireless sensors which will help to monitor behavior and vital functions in a more unobtrusive manner.

Acknowledgment

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