Extended Characterization of Canine Behavior

An application of expert systems

Final Paper - REU Results

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ABSTRACT

In this paper, a software platform utilizing concepts in expert systems is used to automatically estimate canine motion. In modern object searching applications, canines are often used as an effective method for finding bombs, narcotics, and cadavers, due to their superior olfactory senses. However, sight lines from the handler are often required in order to assess whether the canine has found an object of interest. This is often difficult to achieve, as K-9s are often required to find objects in places that the handler cannot access, such as rubble piles, structually unstable buildings, or hostile territory. A reliable method to remotely determine a canine's motion patterns is therefore necessary to ensure the safety of both the canine and the handler. Currently, Canine augmentation technology is allowing for advances in remote determination of behavior in various animals. The development of our canine pose estimation system demonstrates the feasibility of using an automated expert system to reliablely determine canine pose in real time scenarios.

Categories and Subject Descriptors

Software Engineering [**Machine Learning**]: Expert Systems

General Terms

Canine Autonomous Guidance Machine Learner Expert Systems

1. INTRODUCTION

In the last decades, an increasing amount of trained canine (K9) units have been formed across the world, utilizing a canine's natural sense of smell agility to aid in tasks such as search and rescue of trapped personnel, tracking of dangerous chemical compounds such as narcotics and explosives, as well as the search of cadavars. Although the use of canine units have contributed to the success of these searches, the increasing application of these canines in an urban environment brings about new challenges for the handlers' effectiveness. For instance, in a typical searching scenario, a handler would lead the canine through an area where the object is hidden. The canine is trained to recognize the smell of the object it is looking for, such as the scent emitted by C4. Once found, the canine performs a trained response, such as sitting down, to indicate that something of interest has been detected. The handler would then survey the situation and make the corresponding action to solve the problem.

The problem becomes much more difficult in situations in which urban structures are involved. Many situations in urban environments involve locations that could be dangerous for human handlers, such as structurally unsafe buildings, which poses a threat for both the dog and the handler, as well as small spaces in which only the dog can access. Because handlers must have sight lines to the canine at all times to acknowledge that the dog has detected an object of interest, locations of low visiblity such as those significantly impair the effectiveness of these canine units. Without a method for handlers to be aware of the pose of the canine in real time remotely, it is difficult to safely and reliably know if the dog has found something.

Previous work in behaviorial characterization has been done on a number of animals, such as goats, sows, cats, as well as humans. For these applications, post-processed data recorded from a tri-axial accelerometer or two 1-dimensional accelerometers has been the main determinant in the characterization of behavior. Although the data is able to exhibit differences in general behavioral changes (Resting vs Trotting), especially in the more docile animals such as goats and sows, there is significant overlap in subtle changes in behavior, causing the data to be unreliable. In our research, a GPS receiver is introduced to the system, and a sensor suite composing of tri-axial accelerometers, gyroscopes, and magnetometers is used to gather information about the behavior of the dog. The system is mounted on a K-9 trained in bomb searching applications, allowing us to monitor the canine's motion behavior (such as running, walking, sitting) without direct observation of the dog, utilizing sensor data such as 3D acceleration, roll, yaw, and pitch, as well as GPS velocities in order to characterize and estimate the current pose of the dog in real time. Results are validated through both post-processed simulation data using a software platform, as well as real time field trials. A machine learner, specifically an expert system, is used to obtain a generalized method to improve and characterize the motion of the canines.

Auburn University's GPS and Vehicle Dynamics lab has developed Canine Augmentation Technology (CAT) as a method to add technology components that would allow handlers to gain valuable information about the position and orientation of the canine. The project, currently dubbed K9 Project, is aiming to utilize this technology to command, guide, and analyize a trained canine remotely. The system is equipped with GPS and (Inertial Navigation System)INS sensors capable of determining the motion of a canine, allowing estimations of its position, orientation, and pose to be made. The system is also equipped with a command module consisting of a tone-generator and radio that allows commands to be made remotely. Using this system, handlers will be able to determine if a detection has been made remotely, as well as send commands to the dog when necessary.

The Canine Pose Estimator is a system used in conjunction with the K9 Project to determine pose of a canine in real time using machine learning methods. Using human guidance, the system is able to extract characteristic parameters of a pose from the sensor data, allowing the system to learn from the handler's decisions. Given sufficent training, the system should be able to reilably determine pose of any canine. Using this system, handlers can adapt a great number of canines to this system with accurate and reliable pose determination, allowing widespread use of this system for all types of canines, and even other animals.

The following sections will be discussing the following: Section 2 will be a literary review of current technologies and research projects regarding implementations using GPS/INS systems on domestic animals. Section 3 presents the system implemented on the K9 Project, and discuss some of the methods and results of the command and navigation module of the project. Section 4 will discuss the Canine Pose Estimator, it's current progress, and further implementation goals of the system.

2. RELATED WORK

2.1 Detailed Feline behavior

2.1.1 Introduction

A study was performed in Japan (2005) that was cited in all of the subsequent articles in this literary review. A domestic cat's motions patterns was recorded using an accelerometer as a way to provide a method for long term, quanitative observation of animals. Although technology such as VHF radios are available to track an animal. The cost of implementation in manual labor required poses a serious problem to most researchers. With the advances of technology and miniaturization, accelerometers and data loggers has become a viable method of tracking the behavior of animals[1].

2.1.2 Methods

An off-the-shelf kit of sensors that include depth, temperature, and dual-axis accelerometers is used in conjuction with a data logger to record acceleration in one axis, providing data in the surging forward/backward motion of the cat. The system is attached to the throat of the cat using a collar, and the cat was left free to wander indoors or outdoors. Figure 1 demonstrates the range of motion the cat performs, and the expected orientation of the accelerometer.Video data is collected if the cat performs a unique action. After the data is collected. A number of computational methods were tested to classify a range of behaviors. Using these methods, the feline's behavior can be classified.

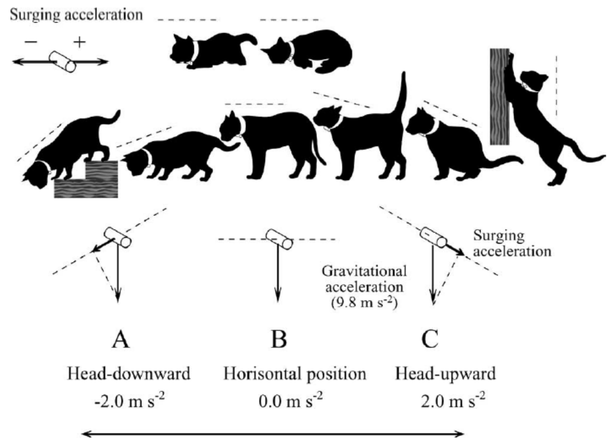

Figure 1: The range of motion that the cat can perform during normal behavior[1]

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2.1.3 Results

With the acceleration data, the group was able to first distinguish the passive/active state of the animal by applying a low-pass filter to the system, as the cat often generated little surging activity while passive. The group also found that the motion pattern of the cat during feeding, eating, and walking followed a cylic pattern, and thus a fast fourier transform (FFT) was used to determine the frequency of these motions. A power spectral density graph is generated, and a characteristic frequency can be found for each of the behaviors modeled. Figures 2 and 3 provides a graphical representation of the data results.

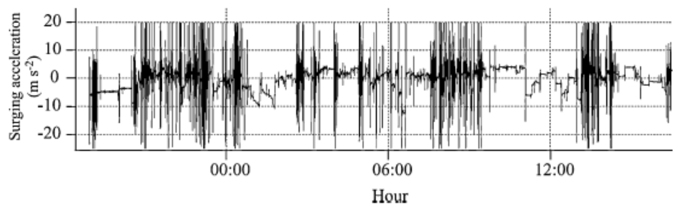

Figure 2: Acceleration data of cat during a single experimental trial[1]

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2.2 Sow activity classification

2.2.1 Introduction

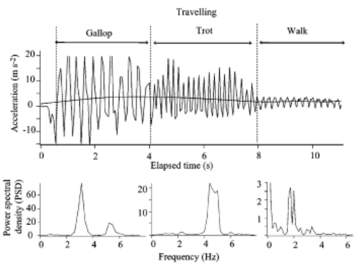

Figure 3: Acceleration Data of each behavior and their cooresponding Power Spectral Density (PSD) Analysis. Notice that each behavior has a unique dominant frequency[1]

A research project performed in Denmark introduced the issue of determining the health of a sow automatically. Since sows are often housed in large groups in farms, it is often difficult to offer individual attention to each sow, leading to significant difficulty in providing proper medical attention to unhealthy sows. By using accelerometers to classify the behavior of the sows, the health of any individual sow can be monitored by analyzing the frequency of various activities. Exception management can then be applied to the system to "pick out" unhealthy sows, such as those that are spending significant amounts of time inactive or not feeding, as well as other notable behaviors, such as when sows are in estrus[2].

2.2.2 Methods

The sow is mounted with a tri-axial accelerometer under the neck of the sow with a data logging device, generating acceleration data at .25hz intervals. Video data, synchronized with the acceleration data, is also collected. The acceleration vector is then calculated from the tri-axial accelerometer using

$$acc = \sqrt{acc_x^2 + acc_y^2 + acc_z^2}$$

and the resulting data analyized in acceleration vs time.

2.2.3 Results

Using the aforementioned system, the group was able to gather acceleration data and analyze the resulting vector vs time. The results, shown in Figure 3, displays a clear difference in the amplitude of the acceleration vector for different activities of the sow.

Using the data, the group modeled the acceleration patterns by using a learning data set, parameterized using a multi-process kalman filter(MPKF). Certain types of motion, such as walking, was analyized using the z axis, since walking is most evidence in the forward/backward direction. In Figure 4, the z axis (forward/backward axis) of the data while the sow is walking is passed through the MPKF and the resulting probabilities of motion are generated. Using this process, the probability of walking reached 1.0 after 40 seconds.

The group was able to distinguish the motions with a good degree of success, with a time window of 1 minute. Although more advanced algorithms, such as a Class II Multi-Process model (West and Harrison, 1997 pp443-456), the

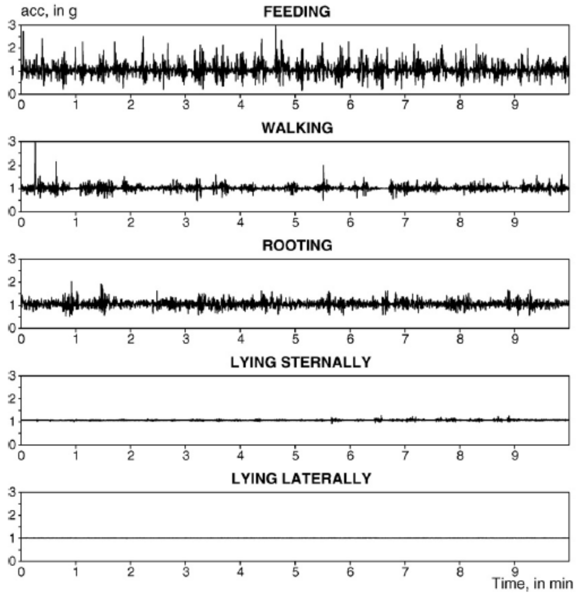

Figure 4: Acceleration vector vs time of the sow in various activities[2]

group states that the increased computations required would reduce the practicality of the system. The group also suggested that the classification of behavior can be accurately and reliably be seperated into two main groups, active(walking, rooting, feeding) vs passive(Lying laterally/sternally).

This paper demonstrated the possibility of classifying motion of an animal using accelerometers by analyzing the acceleration patterns generated using a multi-process kalman filter. The article also pointed out some issues regarding this method, such as difficulty and length of computation, as activities often require upwards of 1 minute for the system to recognize. This suggests that multi-process kalman filters is not a feasible method for determining canine motion in real time.

2.3 Goat grazing patterns

2.3.1 Introduction

Another project using inexpensive tri-axial accelerometers was conducted on a herd of goats on a slightly undulating pasture in Germany, and on rugged mountainous pasture in Oman. A GPS system was also used as a way to track the position of the herd over the course of the study. Using this system, the behavior of the goats and their grazing path can be determined, using the GPS and accelerometer data recorded in the data logger. The data can then be applied to a number of applications, such as the monitoring of a goat's health based on frequency of activity, as well as tracking of a herd's grazing patterns to measure the herd's utility of a pasture's vegetation. This system provides a method of tracking the movement of herds where extended direct observation is difficult to achieve, such as at night, or in mountainous environments[3].

2.3.2 Methods

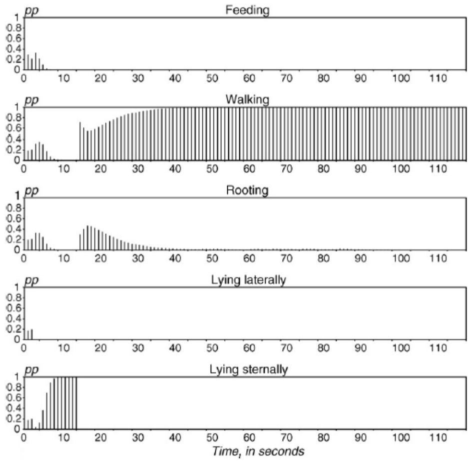

Figure 5: Probabilistic analysis of sow activity, passed through a MPKF [2]

Two goats from Germany and one goat from Omen was used in the experiment, each mounted with a small 18g tri-axial accelerometer setup in the back of the neck. A GPS tracking collar reporting positional data within ± 2.5cm is also used, mounted on the same harness on the animal's neck. The goats in Germany were observed for 5 periods of 4h each at a logging frequency of 1hz; the goat in Omen received 7 periods of 10h each, at a logging frequency of 0.5hz. The GPS module was also added to the goat in Omen with a logging frequency of 0.1hz. During observation, the activity of the goat (resting, eating, walking, other) is manually determined every 10 seconds. In Omen, the position of the head is also determined, due to the difference in terrain between the two tests. The resulting data is then imported into 'Animstat', a C++ based software tool that consists of both a training and analysis module. The training module computes the parameters needed in the analysis module to determine the pose of the goat.

2.3.3 *Results*

After collecting the data, basic analysis of the acceleration vector revealed that the amplitude was large for walking, medium for eating, and low for resting, which reflects the findings of the sow classification paper[2]. The results of the classification can be seen in Figure 5, where the x axis is used to estimate the behavior of the goat. A moving average is computed on the raw acceleration data using the equation

$$mav_n = \frac{dl_{n-m} + \cdots + dl_n + \cdots + dl_{n+m}}{2m+1}$$

where dl_n is defined as

$$dl_n = \sqrt{(l_n - l_{n-1})^2}$$

with l_n being the impulse of the accelerations in each dimension (X, Y, and Z).

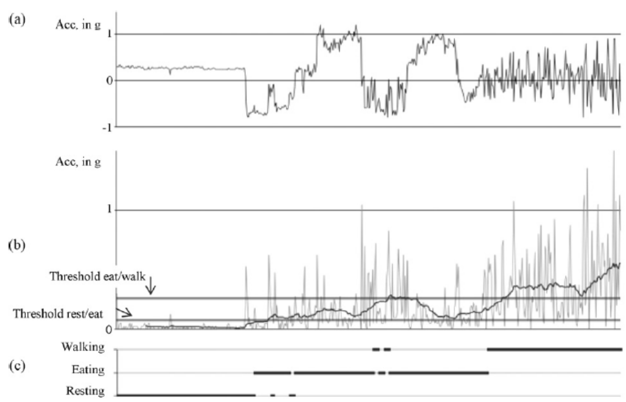

Figure 6: (a) Raw dynamic acceleration data in the x-axis (forward/backward) (b) Calculated moving average (Thick Line) (c) Resulting Classification [3]

Using this method, the automated software is able to classify the motion of the goat, and the results are synchronized with GPS data to map the behavior of the goat with the goat's position at the time. The paper reports that the method used was able to obtain true recognition of resting and eating with >70% accuracy, and with walking at <80% or >120% for 5 out of 11 testing data sets.

This paper demonstrated the possible usage of moving averages as a method for quicker method of classification, and introduces the combined usage of GPS and INS (Inertial Navigation Systems, such as accelerometers) for practical use. However, the paper also points out the inherent issues of using moving averages; Due to the way the amplitude is applied, if the goat goes from resting to walking, the short spike in activity will cause the moving average to calculate a short, but faulty period of eating instead. The paper also addresses the inherent human error involved with the manual logging done to observe the goat's behavior.

2.4 Estimation of Canine pose

2.4.1 *Introduction*

Urban Search and Rescue (USAR) is a field that have seen enormous success in their application of trained canines[4]. Utilizing their superior agility and sense of smell, canines employed in these units are able to pinpoint the position of bodies trapped in rubble, aiding rescue teams and saving precious lives in the process. However, because of the structures involved with USAR, a trained canine must often traverse spaces that a handler cannot follow. This is a major issue, as the only way for a handler to confirm that a body has been found is to receive visual confirmation from the dog. In this paper, a method is discussed that would allow the pose of the canine to be estimated wirelessly using an accelerometer and camera setup transmitted over bluetooth and wifi. Using this system, observers can remotely confirm the canine's searching efforts, greatly extending the operational range of the canine.

2.4.2 *Methods*

A system consisting of 2 dual axis accelerometers is used to determine canine pose. The accelerometers are placed along the spine of the dog, one near the neck and one near the tail. The system uses the duel-axis accelerometer to measure accelerations in forward/backward (x axis), as well as up/down (y axis). From the data collected using the y axis sensors, the pitch of the canine's spine can be determined, allowing for recognition of sitting, lying, as well as movement across inclines. Accelerometer data in the x-axis is used to determine if the canine is walking or stationary. The raw data is transferred to a remote station via bluetooth or wifi systems, and the data is analyized in real time using a heuristic to estimate the pose of the dog.

2.4.3 *Results*

Using the angle of the canine's spine as the primary measurement, the pose estimation of the dog becomes much easier; The inclusion of pitch allowed the motion of the dog to be mutually exclusive, allowing for effective use of conditionals. Using this system, significant differences can be extracted from different poses, allowing for pose to be estimated reliably. However, the author of the paper points out that certain types of behavior, such as walking and sitting, is not uniformly consistent for all dogs, and a system should be developed for generalizing the heuristic for pose estimation for different canines.

3. PROJECT K9 SYSTEM

3.1 Contributions

From the related work, it is determined that there are primarily two issues that exist in animal pose estimation. In the case of the research done by Watanabe, Cornou, and Moreau, [1, 2, 3], the usage of single tri-axial accelerometers proved to be insuffcent at effectively determining complex poses, leading to limited usage. In research done by the USAR [4], an alternate method of accelerometer application was implemented (see 2.4.2), allowing additional parameters to be recorded and more complex pose to be determined. However, a generalized method for implementing pose estimation to multiple canines was not implemented, limited the system's scalability and wide-spread use. The canine pose estimation system extends the work done by these groups by utilizing Project K9's sensor systems, adding on to its capabilities by including a way to determine pose automatically. This is done through the use of an expert system, which is an artifical intelligence system that allows an expert (In our case, it is a canine handler, who would be familiar with classifying the pose of a canine) to teach the system through classification of canine pose as seen in the sensor data. This solves the problem encountered by the USAR researchers, as it will allow the training and use of the canine pose estimator to any canine, as the parameters of pose estimation is generated using a method that is tailored for individual canines.

3.2 About the project

Project K9 aims to create a method for automated guidance of a canine trained in the use of the system[5]. Due to a canine's dynamic locomotion system and innate path finding/obstacle avoidance properties, a canine can easily traverse many types of terrain that current robots would have trouble traversing. A canine trained in the use of our system can therefore become our "vehicle", solving a number of problems regarding locomotion in robots. In exchange, the challenge of this project arises from the inexact movements of the canine, as we cannot directly control the dog's behavior, only influence it. Ideally, a user should be able to designate waypoints for the canine to traverse using a GPS, and the system will guide the canine to each of the waypoints by sending the necessary commands to the dog based on information received from the sensors.

The K9 Project is working with the Auburn Canine Detection Research Institute (CDRI), who has allowed us to use one of their search dogs for this project. Major, seen in figure 7, is a 4-years old male Labrador Retriever, has been trained in traditional field hunting techniques, which allows him to perform "blind retrieves" (Able to find an object without seeing it first and using only commands from the handler) from a distance of up to 100 meters. Additional training of Major has allowed us to command Major using a tone generator and radio system, which emits a tone that Major cooresponds with one of five commands: Stop, Forward, Left, Right, and Recall.

Figure 7: Major the search dog, wearing the sensor vest.

3.3 Materials and Methods

3.3.1 *Sensor Vest*

To equip Major with all of the devices needed for operation, we used a standard dog harness, seen in Figure 8. The vest offers a number of pockets on the left and right side of Major, as well as an auxilary slot at the top. Using the vest, we were able to mount Major with a long-lasting Lithium Ion battery, a control, GPS, and communication module developed inhosue called Rabbit, Tone generator and radio transceiver, which receives and generates tones for Major, the XSens sensor module, and a GPS receiver mounted at the top of the vest. The sensor vest, herein referred to as the Canine Command and Sensor Tracking System (CCSTS), is then deployed on Major during field trials to record data.

3.3.2 *GPS and INS Sensors*

To track the motion of the canine, a GPS/INS system is used to gather the relevent position and orientation data[6]. The INS Sensor, the XSens MTi, contains a tri-axial accelerometer, gyroscope, and magnetometer, which can generate 3D acceleration, tilt, and heading, respectively. The XSens also features an embedded Extended Kalman Filter (EKF) that

Figure 8: Close-up of sensor vest; The GPS receiver and Rabbit electronics board is visible here.

can be utilized to generate self correcting values of roll, pitch, and yaw. The GPS module is a standard GPS receiver capable of reporting position in latitude, longitude and height, as well as estimations of velocity and heading.

3.3.3 *Command and Navigation*

Data collected from the GPS/INS modules is then used to guide the navigation system. By comparing the canine's current position with the position of a waypoint, commands can be made using the tone generator. Once the canine has reached within the vincinity of a waypoint, a stop command is issued, and another waypoint is compared until all waypoints are complete[7]. A diagram of the system can be seen in figure 9.

Unlike traditional vehicles, the canine does not produce predictable motions when commanded; A forward command might yield different motion trajectories, depending on differing field conditions. For instance, a forward command would yield a general forward movement, but might veer to the left or right, depending on if there are objects of interest or obstacles in the way. Therefore, correction tones are applied in an attempt to correct the canine in cases where the dog is too far to the left or right, or if it overshoots the target. If the canine continues in the wrong direction multiple times, a recall is applied and the mission is a failure.

3.4 Canine Pose Estimation

An application of an autonomously guided canine that the group is focusing on is the use of these canines in explosives detection. As part of their training, canines such as Major have been trained to detect the presense of explosives such as C4, and are trained to sit, pointing in the direction of the explosive in lieu of following the current command. Similiar to the work done by canines in USAR, the handler must also receive visual confirmation of this action in order to verify the existance of an explosive. Since autonomous control and navigation of a canine is used as a way to remotely command the dog, line of sight to the dog is not guaranteed. A method for determining the canine's pose using the current system implemented in CCSTS would allow handlers to gain complete awareness of the canine's actions, notifying them if a detection has been made. A software platform, The

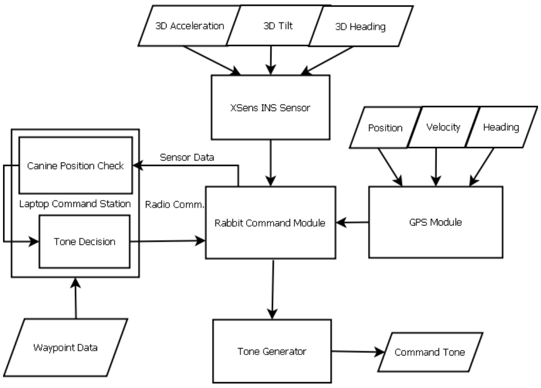

Figure 9: Control system of the CCSTS during autonomous mode.

Canine Pose Estimator, has been created to perform simulation trials of real time pose estimation, as well as refinement of parameters used in the pose estimation heuristic. The system, pictured in figure 10, uses a graphical interface to display sensor data, synchronized with the corresponding video data. The advantage of this system is twofold; The addition of video data allows the user to "train" the pose estimation system, refining its estimation parameters. At the same time, users can visually evaluate the system's effectiveness by comparing the video to the system's estimated pose.

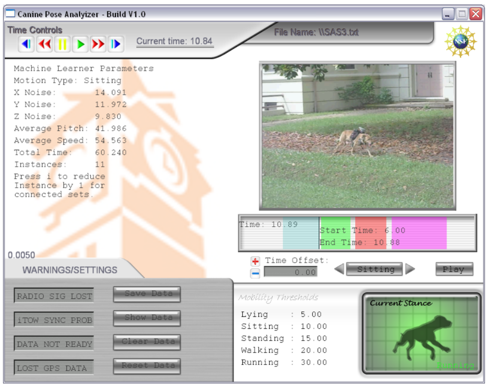

Figure 10: The Canine Pose Estimator system, running a data set in learning mode.

3.4.1 *Machine Learner*

In order for the system to be applicable in the field, it must satisfy a number of requirements, such as reliability, as well as being compatible with a wide range of canines currently employed on the field today[8]. To do this, a system capable of learning and identifying the motion characteristics of any canine is desired. For our implementation, a machine learner utilizing expert system (Human guidance) strategies is used to gather and analyze the necessary information to determine pose. Using a heuristic we've developed for Major, we were able to determine three major components that gave accurate information about pose; Ground Speed, obtained via GPS, Pitch of the dog's spine relative to the ground (XSens), and accerometer noise levels (XSens). Using manually generated parameters, we attempted to determine four total poses, ranging from sitting to running. Although the results of the manually generated heuristic reached acceptable levels of accuracy, it was tedious to adjust, not compatible with other canines, and provided little in terms of proving the system's validity. The machine learner aims to solve these issues by providing a method for any dog trainer to electronically determine their canine's pose by "teaching" the system, guiding the machine learner by correlating sensor data with pose. Once directed, the system generates parameters based on current and previous data using moving averages, and new parameters are formed. The formula for moving averages is listed below:

$$X = \frac{CX * CT + NX * NT}{CT + NT}$$

X = New parameter value
CX = Current parameter value
CT = Total time trained
NX = New data values
NT = Total time represented

Over time, trained parameters should converge to a character set of values, which can be used to compare against real time sensor data. Using this method, we can reliably train the program to observe characterizing patterns made during a certain pose, and use it to correctly determine behavior.

3.4.2 Testing methods

To test for the validity of the machine learner, a number of trials must be recorded to provide the system with parameters that would describe each motion as necessary. Sensor data is recorded in real time using the XSens and GPS modules, and video data is recorded using a digital camera. Using this method, a total of 981 seconds of visual and sensory data is collected, with instances of sitting, standing, walking, running, running uphill, and running downhill. The data is then paired with the cooresponding video file, and training of the machine learner is performed after synchronization of the video and sensor data. Using the system, the user designates time periods where a certain pose appears on screen; the system then calculates the cooresponding batch of sensor data, and produces parameters based on current and previous data. From the recorded data, 308.5 seconds were used to train the machiner (105.56s sitting, 77.32s standing, 44.84s walking, 9.04s running uphill, 62.68s running on flat ground, and 9.08s running downhill), utilizing 1/2 of the files to produce the parameters. Certain motions, such as transitions from one pose to another, are left out to maintain the machine learner's accuracy. Once training is complete to the trainer's satisfaction (At least one minute of each pose), the generated parameter file is applied to the system. Using the parameters, the system defines each motion with a cooresponding range of expected values, and pose is generated based on how closely the incoming sensor data matches with the expected values. Current implementation with the system uses a conditional method to distinguish between poses. A method using expected values using a simple "half and half"' system that encloses a parameter by bridging the gap from a less active pose to a move active pose is currently in development.

3.4.3 Experimental Results

Testing made to current existing data demonstrated the feasibiliy of the machine learner, and it's potential for improvement. Of the 981 seconds of data, 395 seconds were used to compare the effectiveness of each algorithm. Since there was insufficent data collected for uphill and downhill poses, comparisons of those poses were not performed. Table 1 and table 2 shows the results of the experiment in a confusion matrix, comparing the use of manual heuristics versus the machine learner.

Heuristic (Manual Calibration)

TABLE 1	Sitting	Standing	Walking	Running
Sitting	0	4	7	0
Standing	3	0	0	0
Walking	0	0	0	0
Running	0	0	0	0

Machine Learner

TABLE 2	Sitting	Standing	Walking	Running
Sitting	0	4	6	0
Standing	12	0	1	0
Walking	12	4	0	0
Running	0	0	0	0

The first column in the table represents the expected pose (real physical pose) against the actual pose estimated by each system. The higher the value, the more mistakes tended toward toward the combination. Using the matrix, we can identify speific problem areas that require improvement. In this analysis, an error was defined as when pose estimation does not match the visual data, as interpreted by a human operator. Since errors were relatively rare in occurance compared to correct estimations (approximately 1 error per 20 seconds of pose estimation on average for heuristics, and 1 error per 10 seconds of pose estimation for machine learner), the frequency of error was tallied to effectively compare the two algoritms.

3.5 Discussion

From the tables, it can be seen that manual calibration performs more effectively then the machine learner, outperforming it in most conditions, with the most noticable being it's ability to recognize standing and walking correctly more often. Often times, the manual heuristic displays consistancy in pose estimation, while the machine learner often stutters between two poses or briefly display an incorrect pose. There was also an issue where the machine learner would either transition to a new pose slightly earlier or later then the heuristic, although most of the time it is within acceptable boundaries (1 second difference). Despite these shortcomings, it is likely that continued development of the machine learner may be desired, as the machine learner in the current implementation can be improved to include more advanced algorithms, such as the use of statistical probabilities to identify the dominant (most likely) poses, based on how closely the current data matches the machine learner's definitions. Machine learners also possess the advantage of being easy to generalize, allowing for wide spread application once a reliable method is achieved.

3.6 Future work

Future work regarding the use of Machine learners in project K9 and similiar projects can be primarily focused on further optimization of the machine learner pose estimation algorithm, and automating the training data and video synchronization methods. From current experimentation, it becomes evident that in order for machine learners to be more effective, more complex algorithms are needed to achieve the same level of effectiveness as manually adjusting the parameters of the canine. A machine learner that determines the sensor data's closeness with established parameters might be a reliable way to improve the machine learner's effectiveness. Synchronization of data and video through the use of a coupled electronic system may also be desired, as it will vastly improve the quality of human guidance available to the machine learner, allowing for more accurate results.

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