Toward Cyber-Enhanced Working Dogs for Search and Rescue

Alper Bozkurt, David L. Roberts, Barbara L. Sherman, Rita Brugarolas, Sean Mealin, John Majikes, Pu Yang, and Robert Loftin, *North Carolina State University*

A cyber-enabled, computer-mediated communication platform connects human and canine intelligence to achieve a new generation of Cyber-Enhanced Working Dog. CEWDs could be incorporated with other technologies to create intelligent emergency response systems.

After a catastrophic man-made or natural disaster impacts an urban environment, tremendous effort is spent locating and reaching people trapped under rubble. Time is of the essence when it comes to finding survivors. Well-trained search and rescue (SAR) dog and handler teams are becoming increasingly critical in the process of locating survivors rapidly. However, as a consequence of the incredible time, skill, and effort required to train SAR dog and handler teams, they're still relatively inaccessible. Working dogs, depending on their duty, have hundreds of hours of training and conditioning, and can cost between $15,000 and $100,000.[1] Much of this cost is due to the amount of highly skilled labor and time required for training.

SAR dogs, due to their intrinsic cognitive capacity, visual acuity, auditory range, olfactory capability, and survival instinct, are capable of learning to perform a range of remarkable tasks that any current robotic system wouldn't be able to achieve. Some robotics efforts attempt to mimic dogs' locomotion[2] and their olfactory ability to detect components at very low concentrations,[3] but none of these have achieved anywhere even close to canine efficiency and performance. Furthermore, by working with dogs, we get all these capabilities without the challenges of powering, controlling, and developing complex systems. SAR dogs sometimes work on-leash in close proximity to handlers, and other times they're given autonomy off-leash to range out and explore wider areas or climb rubble piles at greater distances from their handlers. Such remote searches require complex and intelligent coordination between dogs, handlers, and first responders. At all times, handlers need to supervise the safety of the environment and look after the welfare of their dogs by continuously reading their body language, looking for signs of anxiety, overheating, or any critical health condition.

To improve the efficiency of SAR training and to augment the current capabilities of SAR teams in the field, we present techniques and technological platforms to enable a new type of Cyber-Enhanced Working Dog. CEWDs are enabled by the use of sensors and actuators worn by dogs forming a

1541-1672/14/$31.00 © 2014 IEEE
Published by the IEEE Computer Society

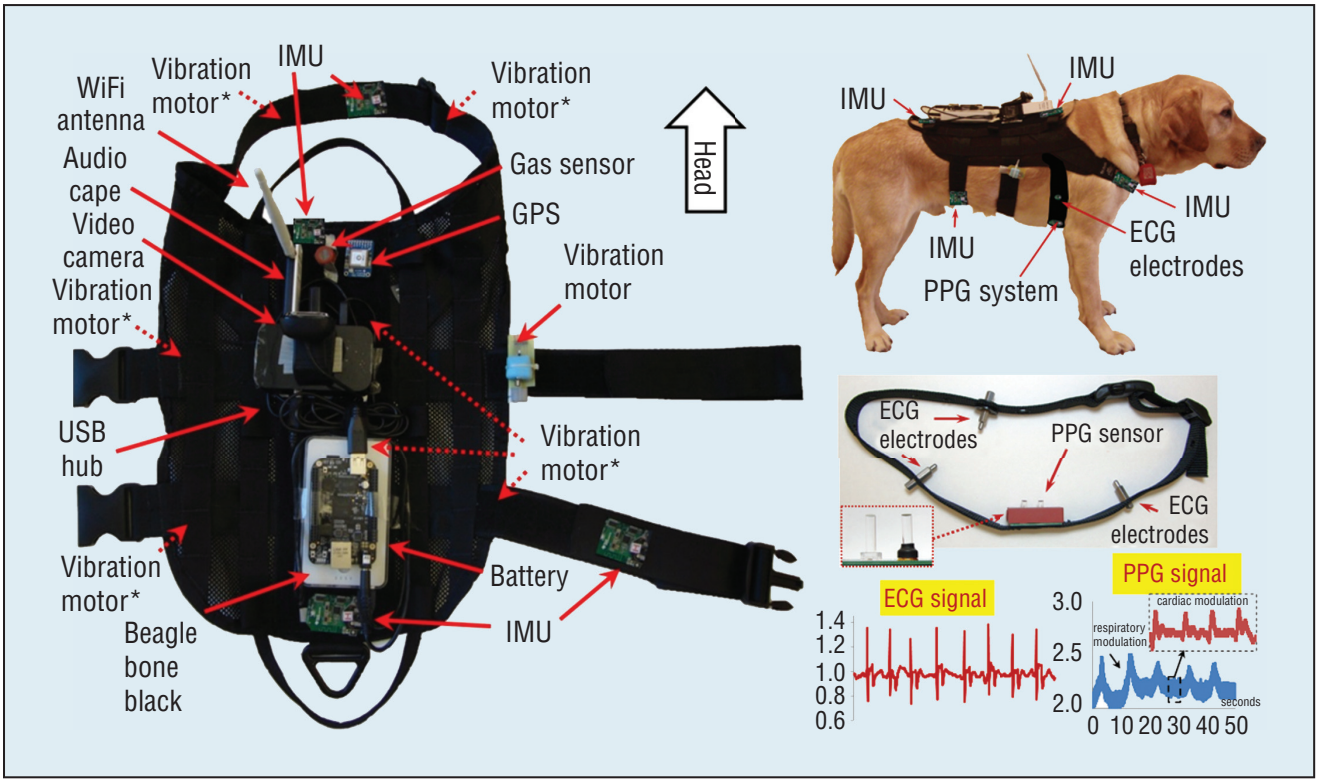


Figure 1. Cyber-Enhanced Working Dog. Top right: the location of inertial measurement units (IMUs) and physiological sensors (detailed in right middle) on CEWD. Bottom right: sample electrocardiogram (ECG) and photoplethysmogram (PPG) signals, where the PPG signal shows both respiratory and cardiac (zoomed in) waveforms. Left: the smart harness platform for remote CEWD handling and environmental monitoring. The * indicates the location of the vibration motors that aren't visible in the picture. The visible motor was exposed for illustration purposes, but is actually located underneath the strap during harness operation.

canine body area network (cBAN) that provides detailed real-time monitoring of the dog and environment. A remote computational node that incorporates intelligent context-aware sensing algorithms and canine models retrieves and interprets the sensor data from the cBAN on the dog and presents meaningful information on dog behavior, physiology, and the working environment to the handler for more intelligent decision making. In addition, CEWDs benefit from a computer-mediated communication between dogs and their handlers, even when they're out of sight or earshot. This canine-machine interface (CMI) would also enable computer-assisted intelligent dog training to speed up learning, reduce the cost of training, and increase the availability of these valuable assets.

Our cBAN consists of a set of sensor and actuator packages attached to a commercial-off-the-shelf (COTS) harness (Figure 1). A centralized control unit on this "smart harness" provides bidirectional communication capability, collecting information from the sensor nodes and communicating this to a remote computer running intelligent behavior classification and training algorithms. We've demonstrated the following capabilities that can be summarized and grouped into three categories:

- *Monitoring the dog*. Wearable inertial measurement units (IMUs) allow computers to detect and recognize posture and behaviors in real time. Furthermore, electrocardiogram (ECG), photoplethysmogram (PPG), and thermocouples enable real-time monitoring of vital signs.
- *Communicating with the dog*. A combination of haptic and aural commands can be sent to dogs using DC vibration motors and a speaker, which enable handlers to instruct their dogs even when out of sight or earshot. Further, using remotely operated treat dispensers enables us (or computers) to reward dogs for desirable behaviors from a distance.
- *Monitoring the environment*. Sensors on the CEWDs (such as GPS, cameras, and microphones) provide handlers with real-time information about potential environmental dangers that confront their working dogs.

These capabilities don't only apply to handler-to-dog communications but also to computer-to-dog communications for many uses of working dogs beyond SAR (guide dogs for the blind,

therapy dogs, guard dogs, and so on). Throughout the rest of this article, we describe our cBAN's design, including results from evaluations where available. We also describe future capabilities that are currently in development.

Base System

All the electronic sensors and actuator technologies constituting the cBAN and connecting human and canine intelligences are currently mounted on a harness. To handle sensor information and communication from handlers, the harness is equipped with a small BeagleBone Black (BBB) computer. The communication link between the central unit and the remote computer is based on IEEE 802.11 transceivers and can be provided by mobile base stations, such as unmanned ground or aerial vehicles (UGV or UAV), during real-life disaster scenarios. Alternatively, the BBB can be outfitted with cellular or other RF communication hardware.

The BBB includes a 1-GHz processor from Texas Instruments (TI; AM3358BZCZ100), 2 Gbytes of onboard flash storage, and 512 Mbytes of DDR3 RAM. It also includes up to 65 general-purpose input/output accessible pins, eight pulse-width modulation (PWM) channels, and eight channels of 12-bit analog to digital converters, which are used to interface with the IMUs, vibration motors, and a variety of environmental sensors, respectively. The BBB runs Ubuntu GNU/Linux, giving access to the utilities and development tools found on a standard GNU/Linux system. Our system uses COTS software for video streaming functionality; however, we developed all the other interface software using Python. Most of our communication protocols are ASCII text to allow as many types of clients as possible to control the system, independent of programming languages or operating systems. In addition, most of the communication to and from the base station is done using User Datagram Protocol (UDP) to increase speed. We include a watchdog program that is responsible for monitoring the wireless connection and other services, and restarting them if they encounter an error or fail to respond. The watchdog program also accepts commands over the wireless connection to allow a base or handheld device to activate, deactivate, or restart any service on demand.

To miniaturize the base system even further, we're in the process of integrating our sensors into a distributed wireless sensor node around the harness. These sensor nodes consist of COTS components that are leveraged on miniaturized flexible printed circuit boards containing a rechargeable battery and antenna unit for short-range signal transmission. Communications between the sensor nodes on the vest and the center unit will come via a lower power Zigbee link provided by TI CC2530 chips, which offer flexible power modes. In the long run, we hope this power conservation can enable recharging batteries on the smart harness through solar or possibly magnetoinductive or biomechanical energy-harvesting systems worn by CEWDs for a self-powered (or at least highly energy-efficient) operation.

Monitoring Dog Behavior and Physiology

SAR dogs are trained to perform certain behaviors, such as pointing, crouching, or lying in sternal recumbency ("cover") near the detection site to inform their handlers that they've detected a specific target odor. These trained behaviors are easily recognized by handlers in close proximity to their working dogs, but with the range CMIs will enable in CEWDs, there's a need to give handlers detailed posture and behavior information in real time, even if the dog is out of sight. In laboratory environments, canine behavior can be monitored using high-resolution video recordings.[4] However, videos are fundamentally limiting for two main reasons: vision-based systems require computationally expensive image processing to autonomously detect canine behavior, and instrumented environments limit where this information can be obtained, making those techniques useless for practical working dog applications.

IMUs offer an alternative to mitigate these problems. Accelerometers, gyroscopes, and magnetometers have been extensively used to monitor activity level in experimental animals in laboratory conditions.[5] Commercially available physiological monitoring systems for canines include accelerometers (www.itstelemetry.com), but these monitors provide processed summary information about physical activity levels, not detailed characteristics of individual behaviors. Commercially available GPS technology has also been used to track a dog's position for sporting applications with a resolution around 0.5 m to 1 m with an accuracy of around 3 m. These systems aren't suitable for indoor use, and only provide very coarse-grained location information without no posture detection capability. There's also some recent work using wearable interactive tactile sensors that can be activated by working dogs with a nose push or gentle bite to send messages to their handlers[6] instead of presenting the detected canine posture via "passive" inertial measurements.

Remote estimation of canine posture and behavior requires collecting and fusing data from multiple IMUs at different locations on the body[7,8] (Figure 1). IMU systems have been used extensively with humans for context awareness and activity profiling in health and exercise-related

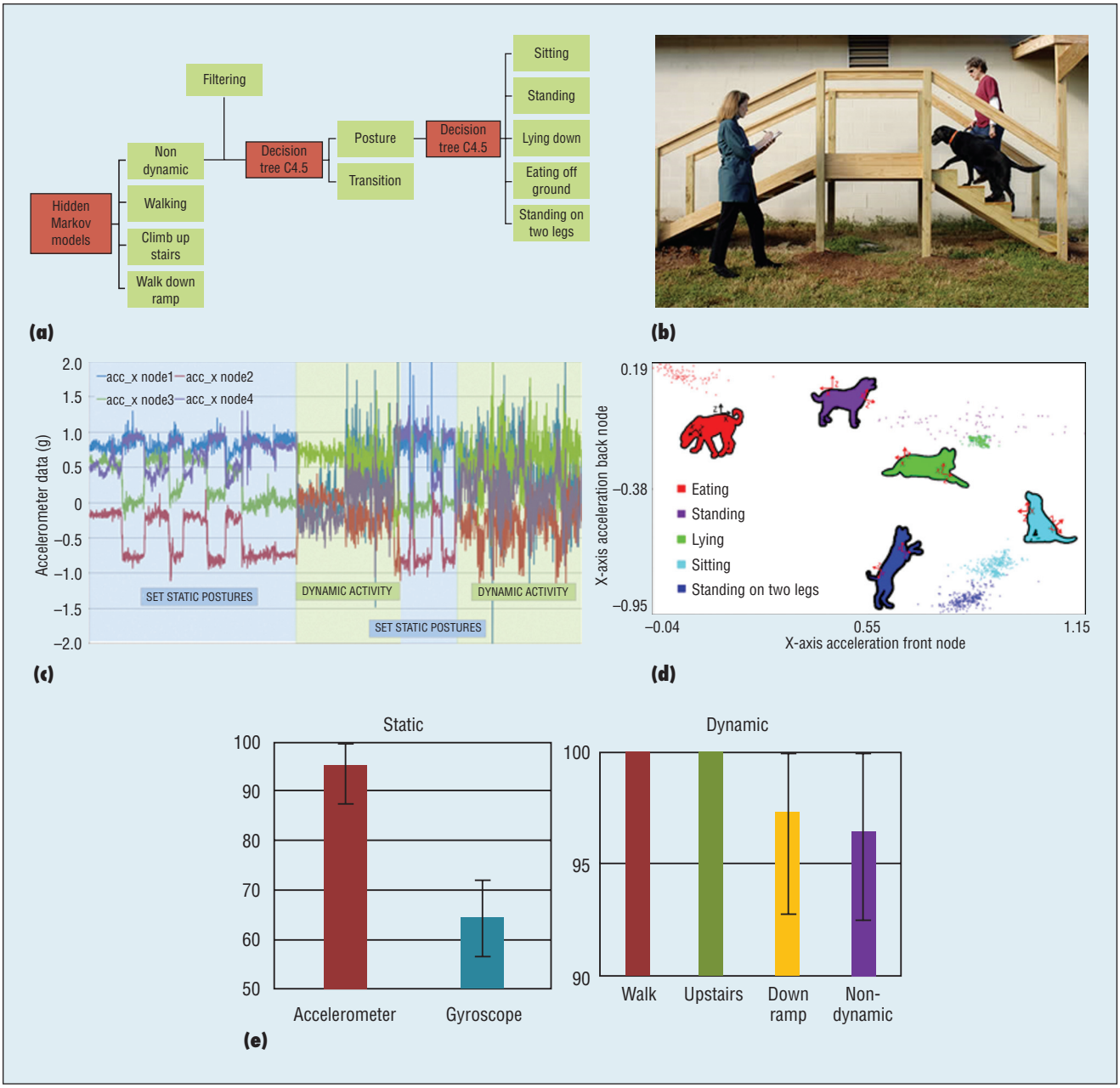


Figure 2. An IMU-based platform. (a) The machine learning algorithm. (b) An experimental set up to test the algorithm. (c) Sample IMU data. (d) Clustering of the data according to static posture. (e) Average accuracies for static and dynamic behavior.

applications and to track the motion and predict the limb positions in real time for neurorehabilitation, digital gaming, and movie production applications (www.xsens.com/en/mtw). Canine posture estimation is a relatively new application area for IMUs, although there has been some limited attempt to use multiple accelerometers to predict the posture of dogs remotely.[9] In that study, heuristic features and angle computation from accelerometer data were used, but the absence of a detailed description of the algorithms and inefficient localization of sensors were limiting.

Our previous work presented an IMU-based platform to detect dogs' postures remotely[7,8] (see Figure 2). In this platform, two sensor nodes were incorporated into the dog's harness, where each node had a MEMS-based, three-axis, ultra-low-power accelerometer from VTI (CMA3000) and a MEMS-based, three-axis, ultra-stable gyroscope from ST Microelectronics (L3G4200) connected to a system-on-chip (TI CC2540) through a serial-peripheral-interface (SPI). The CC2540 combines an 8051 microcontroller

with a high-performance RF transceiver and provides tailored software for use with Bluetooth standards to establish connections with computers and smartphones. We used Matlab to collect, store, and process the inertial data using cascades of machine learning classification algorithms.[8] Such IMU platforms are also available COTS, but tailoring our sensor nodes allows us to further optimize power consumption and achieve three days of continuous operation from a 3-V 225-mAh battery compared to a few hours with COTS systems.

We studied the kinematics of dogs to identify independently moving locations on the body for locating the IMUs,[8] then realized accurate posture estimation by cascading machine learning algorithms (see Figure 2). Based on physical parameters, dog comfort, and algorithm performance, we determined the withers (shoulders), chest, abdomen, and back to be optimized locations. Using data collected from these IMUs, we were able to accurately classify five static postures (sitting, standing, lying down, standing on two legs, and eating off the ground) and three dynamic behaviors (walking, climbing stairs, and walking down ramps) for eight different dogs: three privately owned dogs of different sizes and breeds (Kai Ken, Shiba Inu, and Labrador Retriever) and five dogs from a cohort of Labrador Retrievers being trained to detect improvised explosive devices. All procedures were consistent with National Institutes of Health and US Department of Agriculture guidelines, and were approved by the North Carolina State University's Institutional Animal Care and Use Committee. The accelerometer data include a static and a dynamic acceleration component: the static acceleration represents the projection of gravity over the axis, and the dynamic acceleration is associated with the sensor's actual motion. Gyroscope output corresponds to the angular acceleration, so it becomes meaningful during dynamic activities and is zero during a static posture.

We developed a cascade of three machine learning algorithms and a filtering stage. The first stage of the cascade consists of a set of hidden Markov models (HMMs), each associated with one of the dynamic behaviors of interest. HMMs account for the temporal structure of dynamic behaviors, and each model consists of a set from three to 10 states, along with the probabilities of transitioning and starting at each of the states. HMM parameters were estimated using the iterative Baum-Welch algorithm. The input sensor data that isn't classified as dynamic behavior is filtered with a moving average filter to remove high-frequency noise and is fed to a two-level cascade classifier. Each stage consists of a C4.5 decision tree algorithm. The first level identifies the samples associated with transition behaviors between postures, and the second identifies the postures. Figure 2 shows the classification accuracies using 10-fold cross validation for the two-level decision tree classifiers. For all the reported results, inertial information was logged in the computer while the session was video recorded, and algorithm efficiencies were estimated offline. In these, our approach to classification performed quite well, achieving an average accuracy above 95 percent in all cases (98 percent excluding data from one trial where we suspect the IMUs weren't properly mounted). As expected, the gyroscopes didn't increase posture classification accuracy but were useful for identifying dynamic behaviors. The average accuracy of the HMMs in our model exceeded 96 percent.

Monitoring the emotional status and welfare of dogs in training would yield measurable benefits to their performance and attitude. For example, identifying stressors during the training process could help trainers adjust exposure to challenging environmental conditions to improve learning and reduce the occurrence of fear responses. Behavioral parameters may give clues about emotional states like stress or excitement—the pace, direction, and excursion of a dog's tail wag can indicate an invitation to approach or a caution to give space, for instance. However, these, as well as many other, canine body language communications are subtle and require detailed postural and behavior monitoring. To improve the emotional state interpretation accuracy, behavioral monitoring needs to be correlated with physiological measurements.

The stress induced during the training or handling process has been reported to elicit responses in sympathetic adrenal medullary and hypothalamic pituitary adrenal systems that manifest in cardiovascular, endocrine, renal, gastrointestinal, and hematological parameter changes.[10] The most common methods to measure these responses have been monitoring cardiovascular performance via heart rate and heart rate variability. Respiratory rate might be correlated with dog anxiety as well as physical effort and temperature regulation. Skin temperature is also used to track core body temperature. To obtain consistent and reliable monitoring of dogs' responses to training, we also incorporated physiological sensors into the cBAN to noninvasively measure skin temperature, respiratory rate, heart rate, arterial oxygen saturation, and vocalizations. These physiological sensor nodes on the cBAN contain a surface thermocouple (RTD PT100, Omega), dry ECG contact electrodes, multiwavelength light-emitting diodes (LEDs, Marubeni), photodiodes (TSL13T,

AMS), and fiberoptic light guides to perform oximetry based PPG (see the dashed inlet in Figure 1). The stainless steel ECG electrodes are similar to the metal probes used in a common electronic training collar to avoid shaving the hair at the recording site.

ECG measurements require a differential measurement between three electrodes that were incorporated into a chest strap to collect data from the axillary region, with a reference electrode on the abdomen. PPG detects changes in respiration and cardiac pulse through volumetric measurement. It's obtained optically by shining an infrared light into tissue and detecting the amount of light reflected to the photodiode. The PPG interbeat interval (IBI) at different frequencies provides cardiac and respiration waves as an indicator of autonomic activity, where the mean value and standard deviation of IBI is recorded as additional attributes of the presence of stress or excitement. Sample ECG and PPG signals recorded using our system are shown at the bottom left of Figure 1. The PPG signal demonstrates cardiac and respiratory modulations showing a respiration rate of six breaths per minute when the dog was in deep sleep.

Communicating with the Dog

In addition to developing technologies, we're developing training techniques to teach CEWDs to respond to computer-mediated signals from handlers. Despite the ongoing and significant ethical discussion about their use, electronic (shock) training collars are still the most common remote canine training tool on the market. They typically are used in two different ways. One type of collar is a feedback system without human intervention. The transmitter is controlled by an automatic electronic control system to keep the dog inside a fixed perimeter without physical barriers. The shock stimulus is immediate, contingent, and predictable. A second type of collar involves a manual transmitter that delivers shocks at the press of a button. In this case, human error commonly results in delayed, inappropriate, and unpredictable stimulus. The latter type, in particular, may have a negative impact on behavior and welfare, depending on the handler's skill and attentiveness.[10]

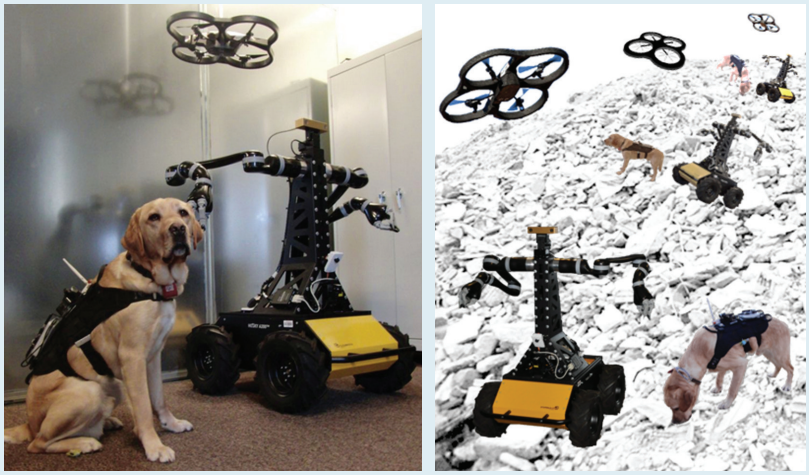
Our CEWD training protocols are based on shaping by successive approximation.[11] Our approach to shaping is completely nonaversive, relying instead on food-based rewards to motivate desirable behaviors. Shaping is a technique used in animal training where desired behaviors are taught to learners by means of selectively requiring actions that are incrementally closer and closer approximations to the desired behavior. Eventually, the action necessary for a reward converges to the goal behavior. Shaping by successive approximation in animal training allows animals to learn much more rapidly than if rewards were given only when the exact target behavior was performed.[11]

To deliver rewards, we use computer-controlled treat dispensers that enable either humans or algorithms implemented on computers to train the dogs. Evaluation of our computer-controlled training algorithms is still ongoing work. But at the time of submission of this article, our algorithms have successfully trained two dogs to perform specific behaviors to receive treats from computer remote dispensers. In these, we also leverage CMIs by training CEWDs to respond to tactile and/or aural cues, where we've incorporated simple aural and haptic communication actuators into the cBAN (Figure 1) to serve as a platform for both human- and computer-trained tasks to be performed without the handler's direct presence.[12] Specifically for SAR applications, we're conditioning dogs to move in seven different directions based on patterns of haptic inputs. Our training pairs the haptic or audio cues with desired behaviors using either human- or machine-delivered rewards. We realize this using a COTS microphone (ADMP401) to record vocalizations, mini-speakers (CMT-1603), and mini-vibration motors (306-109, Precision Micro) to provide training and command signals to dogs. The haptic vibration motors are distributed around the harness in pairs: two motors on each side, one pair on the back of the dog, and one pair in the front across the chest. The amplitude and vibration pattern of these motors is controlled from the cBAN central processing unit using PWM signals. We're in the process of training dogs to perform commands upon feeling the motors activate in specific patterns.

Monitoring the Environment

In addition to the physiological and inertial monitoring described earlier, our platform for CEWDs incorporates a range of environmental monitoring capabilities to help handlers understand the environment the dog is working in.

During disasters, the micro-environment in which CEWDs work could have toxic elements, which would negatively impact both dogs and human survivors. To monitor the environment, we included on the harness a connector to attach different gas sensors for carbon monoxide (MQ-7), hydrogen (MQ-8), methane (MQ-4), and liquidized petroleum gas (MQ-6, from Hanwei electronics). These gas sensors output a voltage proportional to the concentration of the detected gas. Software then



(a) (b)

Figure 3. CEWD working dog and prototype base station. Conceptual depiction of CEWD and a sensor network formed at a disaster site.

reads the digitized value and sends it via UDP packets back to the base station or handheld device. A GPS receiver (MTK3339 from Adafruit) and a forward-pointing video camera (Lifecam HD 3000) are also included to provide location information and improve context awareness. Upon request, the camera streams video to the base station via UDP. Combining the location information provided by the GPS and the terrain information obtained from the camera provides the operator with enough situational awareness to send commands to the canine to direct it to locations of interest. In the future, we plan to incorporate streaming video from UAVs following the CEWDs. The system is also equipped with an audio adapter and speaker allowing the base station to send text to the BBB, where eSpeak (an open source software speech synthesizer vocalizes the message through the speaker. This facilitates communications with nearby people or enables aural commands for the CEWD.

Future Outlook

Our cBAN prototype is fully implemented and has been used for evaluations of posture and behavior estimation, computer training, environmental awareness, and physiological monitoring, but there are still many exciting avenues for future revision to its design, including power budgeting control algorithms, incorporating IMU measurements for noise cancelation in physiological measurements, additional haptic command training, and incorporation of the CEWD harness into disaster response teams. We're in the process of developing an intelligent model-based duty-cycling algorithm that decides which sensors to turn on and communicate with the central unit under what conditions.

A large motivation for our work in developing computer-mediated communication technologies for dogs is to enable not just CEWDs but also to enable richer interactions between dogs and a variety of other cyber-physical technologies that are gaining ground in the disaster recovery world. In particular, computer-mediated communication may enable CEWDs, UAVs, and UGVs to work together in semi-autonomous intelligent teams where unmanned vehicles monitor dogs' positions and physiology, and send action commands. Figure 3 highlights conceptual depictions of our CEWDs with a mobile robot and a drone to provide communications. Although progress is in its early stages, our vision for CEWDs was partially demonstrated under the Smart America Challenge to provide next-generation emergency response capabilities (www.smartamerica.org).

The foundational work described in this article comprises the fundamental physical and algorithmic building blocks of a novel cyber-physical communication platform that enables intelligent computer-mediated two-way communication between working dogs and their handlers. Our goal is to supplement and augment the capabilities—and improve the welfare—of working dogs using an integrated cyber-enhanced dog-handler communication interface to enable handlers to safely work at distances from their dogs. Other applications in which dogs work remotely, such as detection of improvised explosive devices or cadavers, could similarly benefit from this CEWD approach. This system provides novel capabilities: for human handlers to acquire a comprehensive physiological and behavioral picture of their dogs and their dogs' microenvironments in real time; for dogs to acquire clear, nonaversive tactile and auditory inputs from humans to direct their search and ensure their safety; and for computers to perform positive reinforcement-based training. Using computer intelligence to connect human and canine intelligence would amplify the remarkable sensory capacities of SAR dogs that enable them to save lives. ■

Acknowledgments

This work is supported by the US National Science Foundation under the Cyber Physical System Program (1329738). We thank Edgar Lobaton and the members of the ARoS Lab for the use of their Huskybot. The work presented here contributed to a multi-institution partnership of Boeing, Mathworks, National Instruments, University of Washington, MIT Media Lab, University of North Texas, and Worcester Polytechnic Institute to demonstrate a Smart Emergency Response System (SERS) for the Smart America Challenge organized by the Office of Science and Technology Policy under the White House. We thank all SERS team members for their efforts on this work.

THE AUTHORS

Alper Bozkurt is an assistant professor in North Carolina State University's Department of Electrical and Computer Engineering. His research interests include the development of microscale sensors, actuators, and methodologies to interface biological systems for enabling bionic cyber-physical systems with an aim of engineering these systems directly or developing new engineering approaches by learning from these systems. Bozkurt has a PhD from Cornell University for interfacing microtechnologies with metamorphic development of insects for building remotely controlled biobotic organisms (insect cyborgs). Contact him at aybozkur@ncsu.edu.

David L. Roberts is an assistant professor of computer science at North Carolina State University. His research interests lie at the intersection of computation and psychology, with particular emphases on behaviorally inspired algorithm design and on using computation as a window into behavior. Roberts has a PhD in computer science from the College of Computing at the Georgia Institute of Technology. Contact him at robertsd@csc.ncsu.edu.

Barbara L. Sherman is a clinical professor of veterinary behavior at North Carolina State University's College of Veterinary Medicine. Her research interests include quantification of behavior, animal communication, clinical identification, and management of anxieties and fears in companion and working dogs. Sherman has a PhD in zoology with a specialization in animal behavior from the University of North Carolina at Chapel Hill and a DVM from the Ohio State University College of Veterinary Medicine. Contact her at barbara_sherman@ncsu.edu.

Rita Brugarolas is a PhD candidate in the Department of Electrical and Computer Engineering at North Carolina State University. Her interests include wearable technologies for physiological and environmental sensing, low-power medical instrumentation and wireless communications applied to canine-machine interfaces, and human-canine interactions. Brugarolas has a BS in telecommunications engineering from Polytechnic University of Valencia. Contact her at rbrugar@ncsu.edu.

Sean Mealin is a PhD student in the Department of Computer Science at North Carolina State University. His interests include machine learning, wearable computing, and developing techniques to enhance human-canine interaction through technology. Mealin has a BS in computer science from North Carolina State University. Contact him at spmealin@ncsu.edu.

John Majikes is a PhD student at North Carolina State University and a senior software engineer at Oracle. His research interests include machine learning, cyber-physical systems, and medical-device software. Contact him at jjmajike@ncsu.edu.

Pu Yang received his PhD in computer science from North Carolina State University. His research interests include time-series analysis and data mining to identify meaningful patterns indicative of expert knowledge. Yang has an MS in pattern recognition and intelligent systems from Beijing University of Posts and Telecommunications. Contact him at pyang3@ncsu.edu.

Robert Loftin is a PhD student in computer science at North Carolina State University. His research interests include reinforcement learning, interactive learning and activity recognition and prediction. Loftin has a BS in computer science from the Georgia Institute of Technology. Contact him at rtloftin@ncsu.edu.

References

1. W. Konrad, "An Aide for the Disabled, a Companion, and Nice and Furry," *New York Times*, 21 Aug. 2009; www.nytimes.com/2009/08/22/health/22patient.html.
2. M. Raibert et al., *BigDog, the Rough-Terrain Quadruped Robot*, Boston Dynamics, 2005.
3. K. Arshak et al., "A Review of Gas Sensors Employed in Electronic Nose Applications," *Sensor Rev.*, vol. 24, no. 2, 2004, pp. 181–198.
4. P. Martin and P. Bateson, *Measuring Behaviour: An Introductory Guide*, Cambridge Univ. Press, 1993.
5. B. Hansen et al., "Evaluation of an Accelerometer for At-Home Monitoring of Spontaneous Activity in Dogs," *Am. J. Veterinary Research*, vol. 68, no. 5, 2007, pp. 468–475.
6. M. Moore Jackson et al., "FIDO, Facilitating Interactions for Dogs with Occupations: Wearable Dog-Activated Interfaces," *Proc. Int'l Symp. Wearable Interfaces*, 2013, pp. 81–88.
7. R. Brugarolas et al., "Machine Learning Based Posture Estimation for a Wireless Canine Machine Interface," *Proc. Biomedical Wireless Technologies, Networks and Sensing Systems Conf.*, 2012, pp. 3–5.
8. R. Brugarolas et al., "Behavior Recognition Based on Machine Learning Algorithms for a Wireless Canine Machine Interface," *Proc. IEEE Body Sensor Networks Conf.*, 2013, pp. 1–5.
9. C. Ribeiro et al., "Canine Pose Estimation: A Computing for Public Safety Solution," *Proc. Computer and Robot Vision*, 2009, pp. 37–44.
10. B. Beerda et al., "Manifestations of Chronic and Acute Stress in Dogs," *Applied Animal Behaviour Science*, vol. 52, no. 3, 1997, pp. 307–319.
11. B.F. Skinner, *Science and Human Behavior*, Macmillan, 1953, p. 436.
12. J. Miller, G. Flowers, and D. Bevly, "A System for Tracking an Autonomously Controlled Canine," *J. Navigation*, vol. 1, no. 1, 2012, pp. 1–18.

cn *Selected CS articles and columns are also available for free at http://ComputingNow.computer.org.*