Towards a Canine-Human Communication System Based on Head Gestures

Giancarlo Valentin
Joelle Alcaidinho
giancarlo, joelle@gatech.edu

Ayanna Howard
ayanna.howard
@ece.gatech.edu

Melody M. Jackson
Thad Starner
melody, thad@cc.gatech.edu

ABSTRACT
We explored symbolic canine-human communication for working dogs through the use of canine head gestures. We identified a set of seven criteria for selecting head gestures and identified the first four deserving further experimentation. We devised computationally inexpensive mechanisms to prototype the live system from a motion sensor on the dog's collar. Each detected gesture is paired with a predetermined message that is voiced to the humans by a smart phone. We examined the system and proposed gestures in two experiments, one indoors and one outdoors. Experiment A examined both gesture detection accuracy and a dog's ability to perform the gestures using a predetermined routine of cues. Experiment B examined the accuracy of this system on two outdoor working-dog scenarios. The detection mechanism we presented is sufficient to point to improvements into system design and provide valuable insights into which gestures fulfill the seven minimum criteria.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous;

Author Keywords
Wearable technology; Animal-Computer Interaction; Gestures

INTRODUCTION
Working dogs have a specific skill that enables them to perform essential tasks for humans [17]. Working dogs that assist humans with disabilities are called assistance dogs. Other working dog occupations include field work, such as search and rescue (SAR) or explosive-detection.

Despite advances in sensing instrumentation and autonomous systems, working dogs remain a vital necessity in service roles [14]. These roles rely on the ability of dogs to perceive the environment with a great level of detail. This detailed perception can be augmented with occupation-specific training. For example, guide dogs can distinguish between a "wait" obstacle (e.g. car) or "go-around" obstacle (e.g. trashcan) [1]. Explosive-detection dogs can categorize explosives based on chemical characteristics, most notably between "stable" or "unstable" compounds [7].

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Unfortunately, our interviews with practitioners suggest the information perceived by working dogs often exceeds their ability to communicate it to humans. We classify these barriers to communication into three categories.

- Perceptual barriers
- Distance barriers
- Contextual barriers

Perceptual barriers are a result of dogs needing to communicate something they can sense but their human companions cannot. This barrier might be the result of a person's disability (e.g. visual impairment) or a human sensory limitation compared to canines (e.g. scent). Because human senses can't perceive what the dog is sensing, the information *must* be communicated explicitly through the remaining available channels.

Distance barriers are present, for example, in canine-aided search and rescue, where the dogs' communication signals (i.e. barking, positioning, etc.) might be ineffective at distances beyond line of sight or hearing.

Finally, medical alert dogs must often notify humans other than their companions that there is an emergency. Because their signaling behaviors are often only understood by their companions, the alert can be misinterpreted or ignored, possibly delaying medical attention. We call these *contextual barriers*.

In this paper, our focus is to develop methods to overcome the first two communication barriers. As pack animals, dogs have natural gestures to communicate with each other and with humans [2]. Three examples are shown below arranged from representative to generic (Figure 1). *Representative cues* represent the information being conveyed.

Figure 1. The focus of the present study is to find activities usable for generic (symbolic) communication. Individual images reprinted with permission from Jamie Sierra North and Yellow Neener Photography.

For example, a *play-bow* consists of the lowering of the chest to the ground while bringing the front legs out. Play-bows are used to communicate everyday intentions such as the initiation of play (Figure 1a). Note that *representative gestures* can be conceived as equivalent to the *indices of communication* described by Charles Saunders Pierce [13] and brought to the ACI discussion by Mancini et al. [12].

To reduce communication barriers between canines and humans, we propose training dogs to perform generic gestures to generate alerts for cues that a dog has been trained to recognize (Figure 1c). We believe these gestures can be recognized by combining on-line detection algorithms with inertial sensors. (Figure 2).

In the present study, we focus on head gestures detected from a motion sensor on a dog collar. We refer to them as head gestures because they involve head movements but they can be coupled with movements of other parts of the body. We chose the collar placement because canine communication gestures tend to be heavily based on head movements [11]. Furthermore, this selection has the added benefit of representing little additional overhead in terms of equipment worn by the dog. This consideration is important because service dog harnesses vary by organization, police dogs have heavy harnesses already, and search and rescue dogs often wear no harnesses at all.

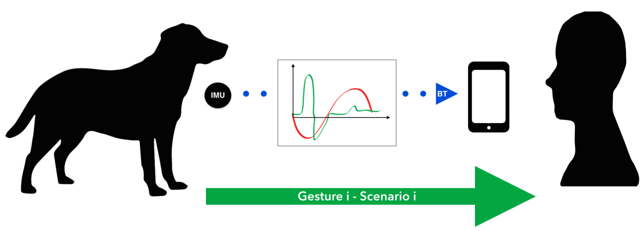


Figure 2. System diagram.

Related Work

Rossi et al. conducted one of the first documented efforts aimed at symbolic dog communication [16]. This "dog at the keyboard project" allowed dogs to ask for objects or activities by pressing keys on a keyboard that produced sounds. Their results showed that "dogs may be able to learn a conventional system of signs associated to specific objects and activities".

In some countries, search and rescue dogs bite brightly colored cylindrical objects called *bringsels* to communicate a find by line of sight [6]. More recently, the FIDO project has explored wearable input devices that dogs can activate by biting, tugging or performing a "nose-touch" as a form of communication [10].

There have also been several previous efforts to recognize canine activities from inertial measurement data. One early effort attempted to detect posture in urban search and rescue (USAR) dogs [14, 15]. The postures were sitting, walking, standing and lying. Here, a rule-based algorithm achieved an accuracy of 76%. A subsequent effort attempted to detect postures as part of an automated training system [4, 5]. By recognizing the dog's posture, it was possible for the system to determine if the correct action was performed and whether a reward should be dispensed. Although originally intended for posture estimation, this work has expanded to include non-static activities.

A recent effort in this field was undertaken by researchers at the Culture Lab in Newcastle University [11]. Their experiments were focused on monitoring activities that correspond to healthy behavior traits of pet dogs. Seventeen activities were detected by an offline PCA-based algorithm with an accuracy of 76% using an empirical cumulative distribution for feature scaling. A similar study was conducted at Eötvös Lorand University in Hungary [8]. In an offline analysis a support vector machine classified lying down, sit, gallop and canter with more than 80% for subject independent classification.

While previous systems have focused on offline analysis of activities of daily living, we expand on them by developing an on-line system using a single sensor.

Problem Statement

Our long term goal is to address the informational asymmetry between the large amount of stimuli perceived by working dogs and the fewer options they have to communicate them, we propose using wearable inertial sensors to detect and mediate intentional communication between working dogs and the humans around them. We begin by considering the types of gestures it must detect. Some of the peculiarities that differentiate this problem from traditional work in human activity or gesture recognition are the following:

1. Users are unable to annotate their own data.
2. Users are unable to reposition the sensor if dislodged.
3. Activities are non-periodic and short in duration.
4. Unlike humans, dogs are not expected to modify their behavior to increase true positives or decrease false positives.
5. The gestures must be taught to the participants without verbal descriptors.

METHODOLOGY

Participants

For this pilot study, we recruited three dogs previously trained in allergy alert, assistance, and police work. The demographics of the participants can be observed from Table 1 below.

	S1	S2	S3
Breed	Retriever cross	Border Collie	Belgian Malinois
Training	Assistance	Allergy alert	Explosive-detection
Sex	M	M	M
Age (yrs)	0.5	5	4
Weight (kg)	21.0	21.3	22.23

Table 1. Subject demographics. *Retriever cross* denotes a cross between Labrador retriever and golden retriever.

The skills and occupations of the dogs we recruited are not identical to our target occupations (guide and search and rescue). This difference is based on our recruitment process which emphasized availability and maintaining the integrity of existing training. We selected participants based on:

- Availability of the dogs and their human companion.
- Proximity to the testing location
- Ability to participate without compromising training

System and Equipment

The main piece of equipment used for this study was a commercially available inertial sensor, the WAX9, by Axivity Inc [9]. This unit consists of a 9-axis sensor, including three axes of accelerometer, gyroscope and magnetometer. Only the accelerometer and gyroscope (on the collar) were used during this study.

We selected the WAX9 due to its light weight compared to sensors with similar capabilities. Considerations of weight were extremely important because a heavy object might obstruct the intended movements.

The unit was strapped with two rubber bands (Figure 3) and padded with polyurethane foam to avoid any movement relative to the collar. The position and orientation remained consistent for all subjects. For stability, the collar was placed above an existing flat collar.

(a) WAX9 (b) Application.

Figure 3. WAX9 inertial sensor attached to dog collar by two rubber bands supported by an equally sized polyurethane foam piece.

We used a companion application on a smart-phone (i.e. Nexus 4) running the Android 4.4.4 operating system throughout this experiment. It received sensor readings via a Bluetooth connection and played synthesized audio messages of the gesture being performed. The gesture messages were voiced by the Android Text-To-Speech (TTS) engine. If the device went out of range, or more than 5 samples were skipped, a corresponding message was also communicated. This mechanism was necessary to distinguish between lack of connection and lack of detecting a gesture. The smart-phone application illustrated a silhouette image corresponding to the basic actions as a supplemental device for dog handlers participating in this experiment.

Gestures Attempted

We selected gestures based on the need to balance seven potentially conflicting criteria (Figure 4). Despite these criteria being similar to the requirements for human gesture detection, their consequences were reflected differently in dogs.

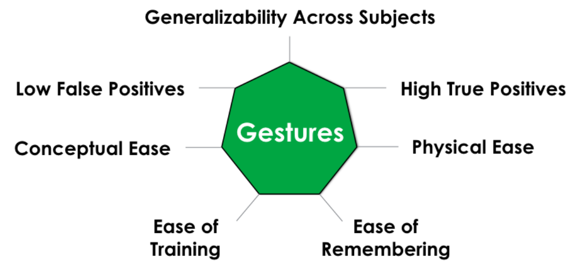


Figure 4. Ideal characteristics of gestures for detection. For canines, the ease of training aspects is of utmost importance.

The first criteria is generalizability across subjects. This criteria meant that we could not rely on gestures that could only be performed by a single participant and considered exceptional even among dogs of a given occupation.

The balance between true and false positives represented the second and third criteria. Unlike humans carrying their phones outside their back pocket to avoid accidental calls (false positives), dogs are not expected to modify their behavior to avoid triggering a certain action. Similarly, unlike humans attempting to speak clearly and slowly to a voice recognition system, dogs are not expected to modify their behavior to increase recognition (true positives). In short, the system should work without the dogs being in the recognition loop.

Even if dogs understand the gesture (fourth) they must be able to physically perform it and do so with consistency (fifth). Humans can understand verbal explanations from other humans, while dogs must learn to use gestures from training (sixth). Ultimately, the dog must remember the gesture without constant training (seventh).

For the benefit of our experiment participants, we had to ensure that new gestures did not negate a previously learned behavior.

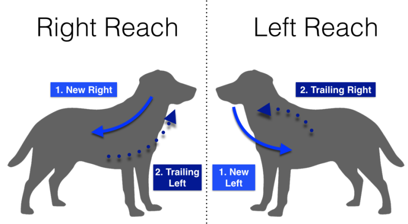
Overall, we relied on gestures the dog could perform in-situ as opposed to gestures that required displacement. Candidate gestures involved horizontal movements of the head ("horizontal gestures"), vertical movements of the head ("vertical gestures"), and the clockwise and counterclockwise rotations (spin and twirl) which we called "rotational gestures" (Figure 5).

Gesture Training Protocol

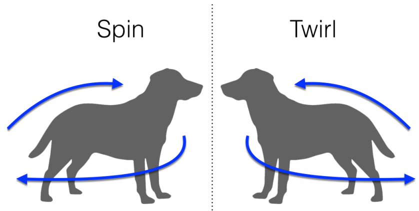
The study discussed in this paper depended on training each subject to perform a set of gestures as described above.

The dogs recruited for this experiment (three) had previous experience in behavior-reward scenarios. They had some familiarity with the basic gestures, such as reaching left (Figure 6), but required training for the timing and sequencing aspects. This training occurred in at most four 30 minutes sessions for each dog. A fourth participant attended only one training session and was not able to subsequently perform the activities.

Trainers requested verbal acknowledgements of the correct completion of the individual basic gestures when dogs performed a longer sequence. This acknowledgement was pro-



(a) Horizontal gestures.



(b) Rotational gestures.

Figure 5. The companion application has a visual representation of the basic activities for the purposes of training. Note that spin and twirl are not only head gestures but also involve body movement.

vided in the same form as the verbal output from the complete gestures.

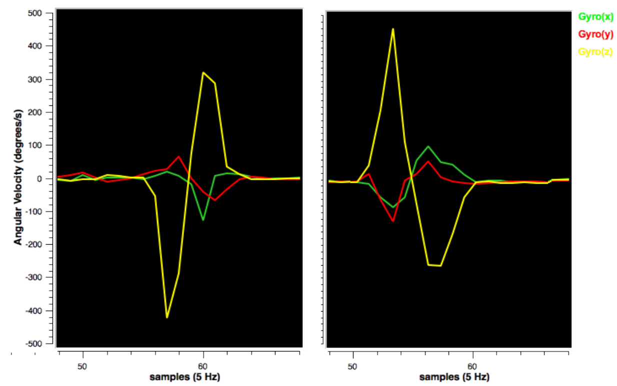
Figure 6. Subject performs the left reach gesture during a training session.

Identification

Gesture Construction

Initially, we graphed the inertial sensor readings from the neck in real time as the dogs performed candidate gestures and movements. The raw readings were stored on the receiving Bluetooth-enabled device (smart-phone or personal computer) for later analysis. Based on their visual representations, we devised a set of rules to capture the desired basic behaviors. These were determined empirically by pilot testing on three dogs. The graphs for reaching left and right can be observed in Figure 7 below.

We devised parameters by asking the dogs to perform the gestures repeatedly to calibrate our rules. In this way, we achieved a satisfactory representation for each basic gesture.



(a) Left reach. (b) Right reach.

Figure 7. Gyroscope measurements for left and right reach with a completely planar movement.

Identification of horizontal gestures

Basic horizontal gestures consisted of turning the head left or right in a way aimed at touching the nose to the middle part of the ribcage area. If the head is moving in a perfect horizontal fashion, this movement will register in the z axis of the gyroscope. When this value ranged between predetermined thresholds (gz<-140 degrees per second), a *left* gesture is detected. As the head is returning to its forward-position (gz>140 dps), a *right* gesture is detected. A combination of *left* and *right* movements in close succession resulted in a *left reach* compound gesture. Similarly, a pair of basic left and right resulted in a *left reach* (Figure 8). As described above, we determined these thresholds by observing the measured movements of three dogs.

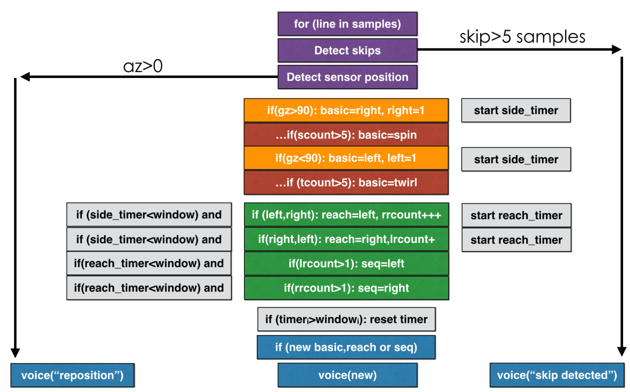


Figure 8. Basic scheme to detect gestures with *gz* representing the z axis of the gyroscope. The behaviors that lead to spin and twirl are not represented.

This scheme assumed no lateral preference ("handedness") on the part of the dogs. Although this assumption did not always hold true, we used the same gestures and thresholds on each side to avoid excessively tailoring to our subjects.

Excluded basic gesture types

Other types of gestures, on which we ultimately did no further experimentation, were vertical gestures, looking up or down. Unlike horizontal gestures, where the motion is short in duration and is rarely sustained, vertical gestures require discrimination between the static *posture* of looking up vs the *movement* of looking up because only the latter would qualify as a gesture. We found that the posture could be determined by the orientation of the sensor, as conveyed by the effect of gravity on the accelerometer readings. To expand beyond posture, we restricted the unit of analysis of all gestures to the transition between one posture and another.

These strategies ultimately proved unsuccessful for several reasons. Vertical gestures proved too difficult to train and perform reliably. In addition, they had a strong propensity for false positives during everyday activity (looking down more so than looking up). The readings also varied by dog size much more so than horizontal gestures. Finally, there was substantial overlap between horizontal and vertical gestures because they are not mutually exclusive. For example, when performing a horizontal gesture, the dog's head will rarely move along a perfectly horizontal plane. Although there are ways to account for this problem, such as redefining the gestures with constraints on all three planes, we postponed such efforts until first testing the simplest set of gesture definitions.

Identification of rotational gestures
Rotational gestures consisted of *spin* and *twirl*. These are: 360 degree rotation to the right and left, respectively. These were detected when a rightward (gz<-90 dps) or leftward (gz >90 dps) motion was detected for a sustained period of time: Each movement was monitored by a variable that expired every second unless a subsequent movement was detected. At the point where five such rightward samples were detected, a spin was recognized. Unlike reaching to the left or right, these gestures do not occur in left-right pairs. Once again, we note that rotational gestures also consists of movement of the body in addition to the head.

Provisional solutions
Along the course of preparing the experiment, we had to provisionally accommodate for two issues not foreseen in the initial design. We describe these solutions for completeness but acknowledge their limited generalizibility for other scenarios.

If the movements exceeded a threshold of 2g as measured by the accelerometer, it was likely that the dog was not in position to perform a gesture. At this point the classifier simply said "too fast" and slept for 1 second rather than making an irrelevant prediction. We determined this threshold provisionally by observing readings over two one hour sessions with two different dogs engaging in high and low intensity activities.

Similarly, if the position of the collar moved, the system voiced a "reposition" command and slept for a second. Misplacement was judged by the z axis of the accelerometer being greater than zero. We discuss a more suitable alternative to improve upon this misplacement in the discussion section.

The time window for the activation criteria is dependent on $seconds * sampling - rate$. For this experiment, the *window* for reaching to the side was set to 3 seconds.

Final Gestures Selected
Based on these experiments, we identified four gestures that deserved further experimentation (Table 2). To differentiate them from everyday movement, we added a repetition component based on similar techniques with humans [3] to the horizontal gestures to arrive at this list.

They are: reaching twice to the left or right side, spinning clockwise (*spin*) and counter-clockwise (*twirl*). One of the constraints we discussed earlier was the ease of remembering a gesture. To take this constraint into account, we established a criteria of no more than two repetitions per gesture. Regardless of whether dogs are able to count repetitions, we only assume they can be trained to perform the current gestures until acknowledgement is provided.

Gesture	Description of gestures
Spin	Clockwise rotation of 360 degrees
Twirl	Counterclockwise rotation of 360 degrees
Right sequence	Reaches to right ribcage two consecutive times
Left sequence	Reaches to left ribcage two consecutive times

Table 2. Sequences composed from basic gestures.

Identification of gesture sequences
When basic actions are consecutively performed within the span of a certain amount of seconds (*window*), a gesture sequence is detected (Figure 9). One example of a gesture sequence is a *double left-reach*. Basic gestures that are not part of the sequence must not be performed while a sequence is in progress, otherwise the counters for compound gesture detection will reset. Note that the basic actions (such as left or right) do not necessarily have to be basic gestures themselves. Both *spin* and *twirl* were composed of movements to the right or left that did not have to meet the threshold for the *right* or *left* gestures in reaching to the side.

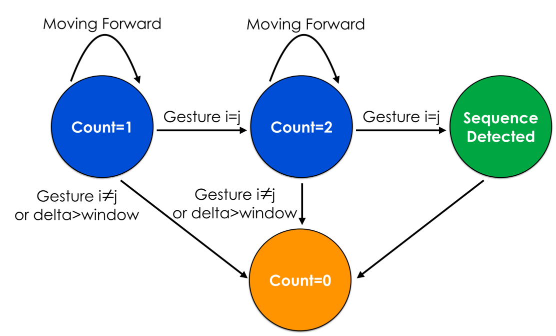


Figure 9. Finite state machine for detecting gesture sequences. Dog trainers refer to these sequences as behavior chains.

Experimental Procedure
To evaluate the proposed gestures and the first prototype of our system, we placed the dog collar with a WAX9 sensor above the manubrium on each one of our participants. The sampling frequency for all measurements was 50 Hz at a range of +/- 2000 dps (degrees per second) and +/- 8g. Each participant was subsequently asked to perform at least six repetitions of each of the gestures by their handler. After completing each gesture, the experimenter provided a food or play reward.

Performance Metrics
We use separate metrics for system detection accuracy and the ease of guiding the dogs to perform the gesture. Beyond

quantifying ease, it is necessary to compute such a metric to accompany the system performance because any failed detection could be attributed to the dog not performing the gesture 'correctly'. For example, it would be unfair to penalize the dog and handler for not performing a gesture on a perfect horizontal plane or at a speed one degree per second less than a required threshold. For this reason, we show how the annotator's scored both system and dog/handler accuracies to give the reader an idea of the breakdown.

Dog accuracy represents how well the handlers were able to guide the dog to perform an activity. For dog accuracy, we associated penalties with ignoring cues, performing the wrong cue or performing a gesture spontaneously. These three items correspond to our deletions, substitutions, insertions, respectively.

Similarly, for system accuracy, penalties were given to gestures undetected, incorrectly detected, or false positives (deletions, substitutions, insertions). All sessions were video recorded and analyzed at a later time to compute the performance metrics (Table 3).

	Dog Accuracy	System Accuracy
Total N	cues given	gestures performed
Deletions	cues ignored	gestures undetected
Substitutions	incorrect activities performed	incorrect detections
Insertions	spontaneous activities	false positives

Table 3. Definitions for performance metrics.

We computed the system's accuracy from the recorded video based on the previous definitions.

$$Accuracy = \frac{N - Substitutions - Insertions - Deletions}{N} \tag{1}$$

System Accuracy Metrics for Sequences
Each result table will contain two columns for tabulating accuracies of the sequence detection. Sequences depended on the correct detection of basic gestures and compound gestures. If a basic gesture was undetected, that deletion would also affect the sequences accuracy (Tables 4,5).

Stage	Time1	Time2
Dog performed	right,left	right,left
Basic detection	right,left	right,left
Compound detection	right reach	right reach
Sequence detection	right sequence	

Table 4. Sequences depended on the correct detection of basic gestures and compound gestures.

Stage	Time1	Time2
Dog performed	right,left	right,left
Basic detection	right,left	right, none
Compound detection	right reach	none detected
Sequence detection	none detected	

Table 5. If one of the basic gestures goes undetected, it affects the accuracy of the sequence detection. For this reason, we reported sequences II by counting cases where the basic units were detected correctly.

To account for this case, we computed a second metric (sequences II) where no penalty was given to the sequences for deletions at the basic level.

Repetition Experiment
The dog handler used a *target stick*, *target toy*, or a food target consisting of a small treat, to give the subjects an indication of how to move their heads. Target sticks are commercially available and are in common use in agility and obedience dog training practice. Although the resulting motions for each target device exhibit some variation, they were considered equivalent for the purpose of this experiment.

False positives in Urban Environment
We tested the system in a more realistic scenario inspired by active service dogs. In particular, we focused on assistance dogs (guide dogs included) who must accompany their handlers as they travel through dense urban environments. Although the leash prevents the testing of gesture detection, this scenario allows for testing of false positives (Figure 10).

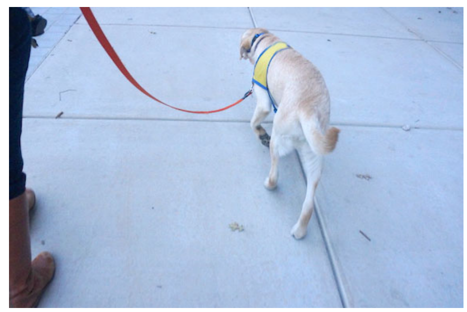


Figure 10. Assistance dog walks through sidewalk while wearing the insrumented collar.

False Positives in Open Environment
For this experiment, we allowed dogs to run off-leash in an open environment. During this time, they were given objects to fetch and retrieve by their handler.

Figure 11. Explosive-detection dog fetching objects in an open environment.

RESULTS

Repetition Experiment

Our evaluation of the accuracy results are summarized below. These were analyzed and computed by a single observer and were subsequently verified by a secondary observer.

	S1	S2	S3
Method	Target stick	Luring	Target toy
Total N	47	48	23
Deletions	0	0	1
Substitutions	8	1	0
Insertions	4	4	1
Accuracy	74%	89%	91%

Table 6. Dog accuracy for each subject. Note that the training methods used were different for each one.

Table 6 shows the ease of guiding the desired gestures in each dog. The most common substitution was spinning when a side reach gesture was being induced. The second most common substitution, particularly for S1, was reaching to the opposite side of the target stick. When performing a sequence, S1 would wait to be rewarded for the first activity and not perform the second repetition. All of the insertions for S1 consisted of attempting to reach the target stick before it was placed on its intended location.

In cases where S1 performed an inserted or substituted gesture, we still evaluated the system's detection. In some cases, the new gesture affected the timing calculation of the more complex gestures and this was scored accordingly (Table 7). For this reason, basic actions (left, right) had the highest accuracy compared to compound (left reach, right reach, spin and twirl) or sequence detection (double left or right reach).

Gestures	Basic	Compound	Sequences I	Sequences II
Total N	82	35	11	11
Deletions	0	2	0	0
Substitutions	7	2	0	0
Insertions	0	3	2	2
Accuracy	91%	80%	82%	82%

Table 7. System accuracy for subject 1. Sequences II analyzes the detection of gestures sequences by controlling for cases where the compound gesture should have been detected.

Most of the system deletions observed with subject 2 (Table 8) can be accounted by two factors. First, the left and right reach gestures were performed using the technique known as *cookie stretches*, a form of luring. When S2 performed the reach, the right motion was detected appropriately. After doing so, he would look downwards to ensure that no part of the target treat was on the floor (Figure 12). At this point, the time-to-live for the initial basic gesture would expire. When the dog finally came back to face the handler, this motion was treated as a new basic gesture, rather than the closing part of an existing one. Not only did this phenomena cause the performed reach to go undetected, but it also caused the subsequent one to be interpreted as the opposite side. For subject S2, this error resulted in 16 system substitutions (Table 8). This behavior also explains the large discrepancy between detection of basic gestures and detection of compound ones.

Dogs trained in occupations requiring constant eye contact with their handlers maintained it as much as physically possible while performing the gestures. This behavior was not foreseen in the design of our identification method or experiment. If the head is vertically oriented (e.g. looking at the handler) the movement will be increasingly reflected in the x axis of the gyroscope. Nonetheless, horizontal movements are rarely aligned perfectly along a single axis. To account for this issue, we subsequently combined the z axis readings of the gyroscope with the x axis readings, by taking the Euclidean distance between each of the two points and keeping the sign of the z-axis. Below are the results of this modification on testing with subject S3 (Table 9).

Gestures	Basic	Compound	Sequences I	Sequences II
Total N	47	36	14	5
Deletions	0	1	9	0
Substitutions	5	16	0	0
Insertions	1	3	2	0
Accuracy	87%	44%	%36	%100

Table 8. System accuracy for subject 2. Sequences II analyzes the detection of gestures sequences by controlling for cases where the compound gesture should have been detected.

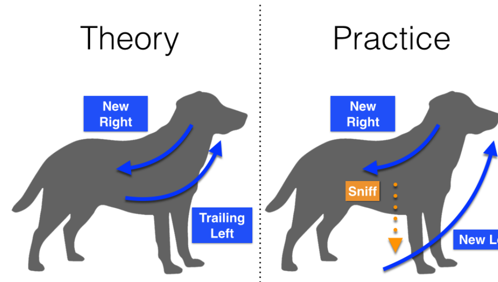


Figure 12. The use of a treat to lure the reach behavior caused problems detecting the gesture.

Gestures	Basic	Compound	Sequences I	Sequences II
Total N	49	20	5	5
Deletions	0	2	0	0
Substitutions	0	2	0	0
Insertions	0	3	1	1
Accuracy	100%	85%	80%	80%

Table 9. System accuracy for subject 3. In this case, gz and gx were combined.

False Positive Experiment

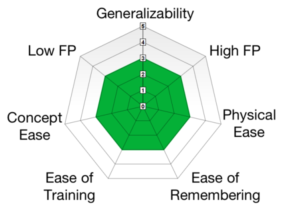
We performed the false positive experiment with three dogs (S1, S2, S3), under different conditions under which no gesture should activate. The results of these experiments are summarized below (Table 10).

	Session 1	Session 2	Session 3	Session 4
Dog	S1	S1	S2	S3
Duration	15 mins	60 mins	15 mins	15 mins
Scenario	Stairs, walking crossing street	Stairs, car travel, play	Open, play	Open, play
False Positive	Spin(1) Left Reach(1)	Left sequence(2)	Down (4)	Left Reach(1)
Cause	Collar moved vigorous shake	Repetitive left movements while going down-stairs	Looking up while chasing object	Running and turning

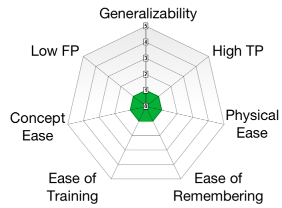
Table 10. False positives experiment. The up and down gestures triggered much more so than the other, while still being difficult to perform. For this reason they were not included in the repetition experiments.

DISCUSSION

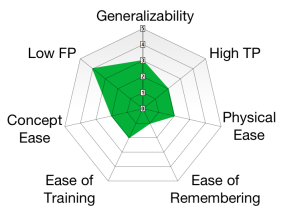
We can now compare the benefits and drawbacks of each gesture type along the seven constraints we described earlier. Although not all the axes are quantifiable yet, our subjective experience has allowed us illustrate them in provisional form (Figure 13). Although the given scores can change when testing a greater number of dogs of different backgrounds, they represent our understanding at the end of the current experiment.



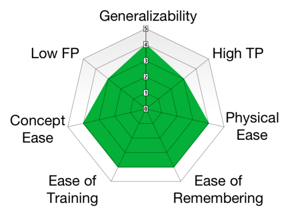
(a) Single horizontal gestures (baseline).



(b) Vertical gestures.



(c) Double horizontal gestures.



(d) Rotational gestures.

Figure 13. Gesture qualities relative to single horizontal gestures, which serve as a baseline.

Experimental Improvements

An experimental flaw in the lack of counterbalancing resulted in most twirls being performed before or after a spin. It is possible that this fact caused their identification to be different than they would be otherwise.

One way we have tried to eliminate the use of target sticks and *cookie stretch*-luring is to design clear markers of the locations to be targeted. These markers allow both the dog and the handler to train gestures with more precision.

As mentioned earlier, assistance dogs mostly work on-leash in an outdoors environment. The training should occur on-leash from the first practice session through the last. This requirement will ensure that the gestures selected are feasible for use while on or off-leash.

System Improvements

One area of improvement is the sensitivity to orientation. This identification procedure assumes the sensor remains below the head when the gestures are being performed. Positioning was particularly difficult in dogs with a smooth coat, (e.g. S3), in which the collar tended to rotate and slide freely. Even though the effect of gravity favors the center position, the sensor still shifted for a non-trivial amount of time as a result of vigorous activity.

A more suitable alternative to improve upon this misplacement would be to calculate the tilt angle of the sensor based on the effect of gravity on the accelerometer readings and recalibrate the gyroscope readings with the 3x3 rotation matrix corresponding to "virtually repositioning" the sensor.

CONCLUSION

In this manuscript we illustrated the use of an on-line communication system for working dogs based on head gestures detected by an inertial sensor placed on the collar. Our preliminary results show the type of gestures that can allow humans to receive vital information from working dogs.

In this effort we have taken the first step in gesture recognition for dogs. We have shown the importance of considering the devices the dog is already wearing such as a leash, harness or existing collar when selecting the gestures. We also have to consider how dogs are trained (e.g. the effects of dropped treats). In our future works, we will account for these factors by collecting a database of everyday canine activities so as to select gestures that do not interfere with them. By collecting this database we can then choose gestures that are appropriate and start employing more sophisticated machine learning techniques that are conducive to the task.

ANIMAL CARE

The training of the gestures relied exclusively on positive reinforcement techniques. These studies were conducted in accordance with the Institutional Animal Care and Use Committee (IACUC).

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