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Measuring and analyzing canine movement through 2D video in relation to their trainability

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Abstract. This study introduces a novel approach for quantifying and analyzing canine movement through 2D video recordings, aiming to elucidate the relationship between dog movement patterns and their trainability responding to abandonment stimuli. Utilizing an advanced method based on deep learning, we captured and estimated 24 3D-markers of nine Siberian Husky dogs performing the 3-minute task in their daily environments. From the markers captured over the skeletons, the average amount of relative motion was calculated for three sub-phases: “initial”, “intermediate” and “final”, for the two trials performed on each dog. The core objective was to determine how specific motion patterns correlate with different levels of training across sub-phases. Preliminary findings suggest that -the second subphase is more associated with the levels of trainability based on the dispersion between the two trials-, as an indicator of a dogs’ potential for trainability. This research not only contributes to the understanding of canine motion patterns during this specific test but also offers a scalable and non-invasive tool for professionals and dog owners to enhance training outcomes based on individual motion profiles. **Keywords:** Motion tracking, canine trainability, motion analysis, movement patterns.

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1 Introduction

Dogs exhibit a wide spectrum of behaviors that reflect their welfare in many ways, such as emotions, cognitive abilities, and social aspects. These behaviors range from the playful actions observed during activities to more structured responses during training sessions. Understanding these behaviors is crucial since it allows us to have a clear picture of the current state of the dog, leading to more effective communication and training strategies (de Castro et al., 2020).

Trainability in dogs encompasses more than just the ability to follow commands; it reflects a complex combination of genetics, environmental influences, and individual temperament and personality Van der Waaij et al., 2008; Jones & Gosling, 2005; Serpell & Hsu, 2005; Ruefenacht et al., 2002). These traits are what makes some of the dogs excel in obedience, while others show remarkable skills in tasks such as search and rescue or even medical and emotional support. However, accurately assessing trainability can be challenging, as it requires a nuanced understanding of each dogs’ unique responses to a variety of training stimuli and situations (Bray et al., 2021).

Specific body postures and movements, such as tail position, ear orientation, and the dogs' overall body alignment, have been shown to play a crucial role in their receptiveness and ability to engage in training sessions (Andrukonis, Protopopova, Schroeder, & Hall, 2023). For example, dogs exhibiting relaxed and attentive body language, forward-facing ears or a wagging tail, are often more responsive and capable of forming positive associations with training cues (Deldalle & Gaunet, 2014). On the contrary, signs of stress or discomfort, indicated by a lowered body posture, tucked tail, or pinned ears, can negatively affect a dog's learning process (Duranton & Horowitz, 2019). These findings emphasize the need for trainers to understand and respond to canine body language to facilitate effective training.

Historically, canine behavior has been studied by direct observation by trainers and behaviorists. Although effective to a degree, these methods are time-consuming and often fail to capture the subtleties of canine behavior due to unreliable or biased interpretations. This creates a need to develop objective and precise methods that help in the process of measuring a trainability score. Consequently, this research aims to investigate the correlation between dogs' physical reactions to an emotionally charged stimulus and their trainability score assigned by experts, by analyzing canine movements through 2D video analysis.

This approach not only has the objective of automating the process of assessing trainability, making it more efficient and objective, but also unveils patterns and nuances in canine behavior that may be invisible to the naked eye, gaining deeper insight into the factors that influence a dog's ability to learn and respond to stimuli, improving the process of trainability and enhancing the human-canine bond (Bray et al., 2021; Arnold, 2016).

Very few studies have addressed the automatic detection of postures or the tracking of canine movement with the aim of associating them with emotional stimuli or even with trainability. For instance, key physical landmarks on dogs, such as tail position, ear orientation, and overall body posture, have been identified to recognize patterns associated with different emotions. By leveraging machine learning techniques, the authors aim to develop a predictive model that can accurately identify canine emotions based on these physical indicators (Ferres, Schloesser, & Gloor, 2022).

Our work diverges significantly from existing studies in the field of canine behavior analysis, particularly in the observation and analysis of dogs in their natural environments. Although a considerable amount of previous work has relied on controlled settings or static images from online databases, our approach prioritizes the authenticity and dynamism of real-world interactions. By capturing video footage of dogs responding to abandonment stimuli in their usual surroundings, we ensure that our data reflects the variability of behavior. Based on real-life observations, we set a new standard for research in understanding and improving the training process of dogs.

Advancements in artificial vision and machine learning algorithms allow for the development of intelligent systems for analyzing animal behavior, especially in terms of their movements. Through the lens of artificial vision, we look to decode the subtle nuances of how dogs convey information and interact with their surroundings in a naturalistic manner. This interdisciplinary approach not only contributes to a deeper understanding of animal communication, but also opens the door to the creation of innovative technologies that seek to facilitate human-dog interaction.

This study is part of the Tzuku project, initiated by a collaborative consortium of Mexican institutions and supported by funding from the National Council of Humanities, Sciences, and Technologies of Mexico. The overarching objective of the Tzuku project is the development and refinement of technology to optimize the selection, training, and operational procedures related to search and assistance dogs. Within this framework, an investigation of the vocal and physical behavior patterns exhibited by dogs in various internal states is conducted, which encompasses the realms of physical well-being, emotional disposition, and contextual interactions. These findings serve as the foundation for the development of sophisticated computational models designed to discern and interpret canine behavior in different data sources such as heart rate (Ospina-De la Cruz et al., 2023), images (Hernández-Luquin et al., 2022), vocalizations (Abrego-Ulloa et al., 2022), and video (Chavez-Guerrero, Pérez-Espinosa, Puga-Nathal, & Reyes-Meza, 2022). The resultant computational frameworks offer actionable insights and invaluable guidance to a diverse array of stakeholders, including dog owners, caregivers, veterinarians, trainers, and individuals with disabilities, facilitating informed decision-making processes.

2 Experimental procedures

We collected data from 9 Siberian Husky dogs (3 males and 6 females), dogs were 1 to 6 years old. The experimental protocol was approved by the Bioethics and Academic Committee of the Postgraduate Program in Biological Sciences at the Autonomous

University of Tlaxcala. Owners signed an informed consent for their dogs to participate in this study. The behavioral test was conducted at the owner's residence on two different days. Three video cameras were used to record the dogs' behavior from multiple angles during the test. For each test, a 2-minute recording was made before the stimulus was applied to capture the dogs' usual behavior. Subsequently, the stimulus was applied for three minutes and the recording continued for 2 minutes after the stimulus ended.

We applied twice (Trial 1 and 2) a task called Abandonment, performed as described here: the dog was removed from its usual living area and tied to a post or tree in the shade. The owner was instructed to secure the dog to the post and then depart from the location. This stimulus lasted three minutes. During this test, the dogs wore a small sensor to record their heart rate (polar OH1) in the ventral area and were recorded with a thermographic camera (Fluke TiS75+) to register changes in their surface temperature. Nonetheless, this data was not utilized in the current study.

2.1 Labeling-tracking

0 - Left Front Paw	12 - Tail Set
1 - Left Front Wrist	13 - Tail Tip
2 - Left Front Elbow	14 Left Base Ear
3 - Left Back Paw	15 - Right Base Ear
4 - Left Back Wrist	16 - Nose
5 - Left Back Elbow	17 - Chin
6 - Right Front Paw	18 - Left Tip Ear
7 - Right Front Wrist	19 - Right Tip Ear
8 - Right Front Elbow	20 - Left Eye
9 - Right Back Paw	21 - Right Eye
10 - Right Back Wrist	22 - Withers
11 - Right Back Elbow	23 - Throat

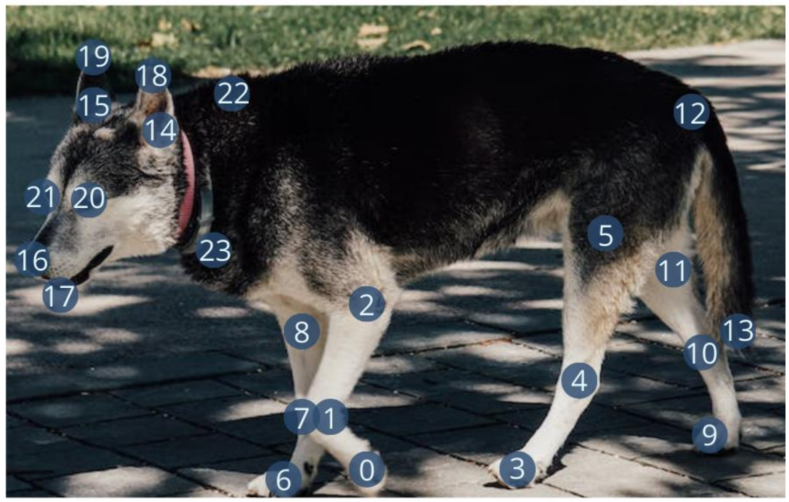


Fig. 1. List of markers used to train and process the videos through DeepLabCut, inspired Ferres et al. (2022) selection of landmarks.

In previous research done by Ferres, Schloesser, and Gloor (2022), landmarks in dog postures were effectively used to detect emotions such as anger, fear, and happiness, by using a 24-point distribution base as illustrated in Figure 1. These points were strategically placed in key anatomical locations, where dogs can exhibit cues that lead to the recognition of an emotional state, with an example being the "play" posture, where the dog stretches its paws out, often associated with a positive emotion. This posture can vary between dogs, so a detailed analysis of all movements of the paws, face, and tail is needed to ensure a correct classification. In this comprehensive study, depicted in Figure 2, we compiled the landmark detection process and subsequent data analysis to delve into the nuances of trainability. A detailed explanation of each of these steps will be described in the following paragraphs.

This study also used DeepLabCut (DLC), a landmark detection software by Mathis et al. (2018). This framework can help to precisely label using machine learning models. After doing practical examples in this tool and a brief analysis, we opted to apply Transfer Learning techniques to enhance our model's performance. This was done using ModelZoo's SuperAnimal-Quadruped model (Ye et al., 2023), chosen for its similarity to landmark suggestions in Ferres, Schloesser, and Gloor (2022). This model has been trained on various animals and scenarios, including different breeds of dogs.

For our training dataset, we employed DeepLabCut's tools to extract and label approximately 20 frames per video from our collection, totaling 200 frames from different dogs and stimuli, these frames are later augmented using DLCs recommended method (imgaug). Our model was then trained for 200,000 iterations, as it is the recommended amount by both the authors and the community. Then, we performed an outlier removal method to obtain even more frames for the dataset. After extracting outliers for half of the videos in the dataset, we resumed training for the model, resulting in our model training for 300,000 iterations.

We evaluated each dog by applying four positive and four negative tasks, subsequently, we measured their behaviors during tasks and assigned each dog a score according to its performance. For example, the owner was instructed to engage in play with the dog using their favorite toy, object, or in the way he normally plays with his dog, then we assigned 0 if the dog lay down or 1 if the dog followed its owner, wagged its tail or stood on two legs. We analyze all the behaviors displayed in the positive and negative tasks and, at the end, we calculate the points obtained by each dog.

We use the abandonment task because it determines the level of dog independence (which is an important feature of trainability). Furthermore, tethering the dog during the test minimized its chances of moving out of the camera's view, thereby aiding the tool in more effectively extracting all markers.

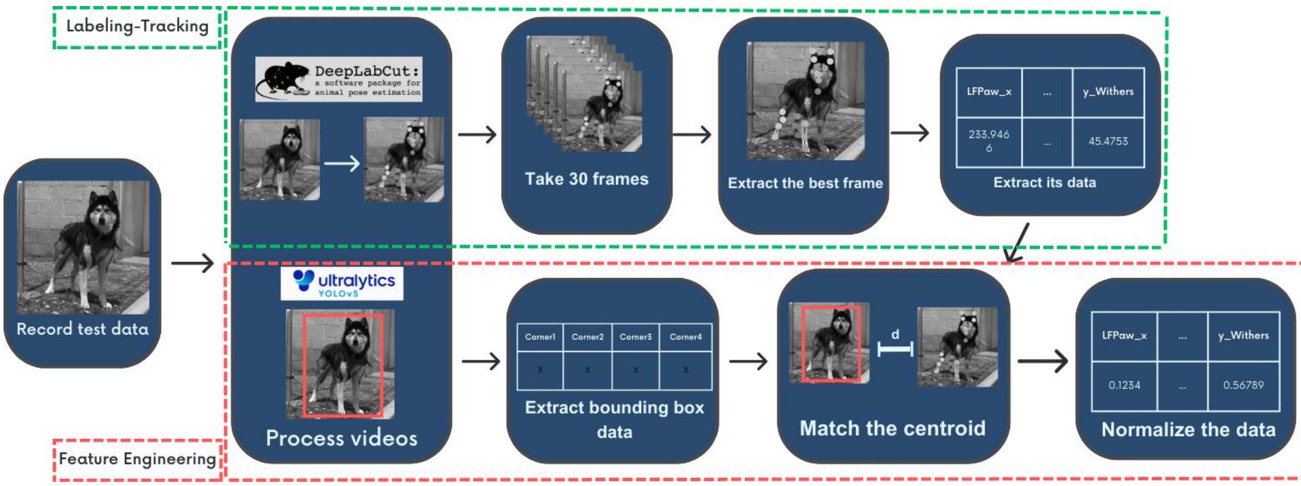


Fig. 2. Methodological process to obtain the normalized landmarks from videos.

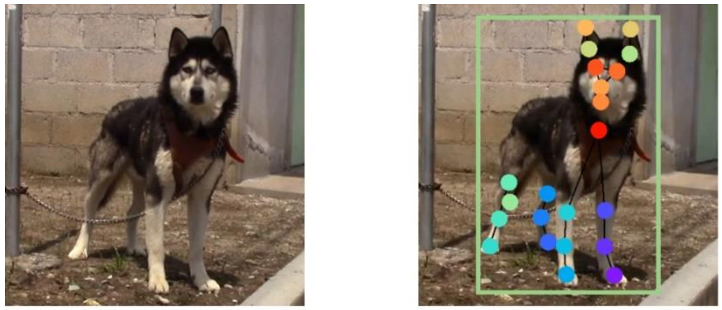
2.2 Feature engineering

Given the naturalistic conditions under which the experiments were conducted, several variables could potentially impact the accuracy of our DeepLabCut (DLC) model. Specifically, the dogs' varying distances and angles relative to the camera, along with possible occlusions caused by bushes and other environmental elements, represented significant challenges. To address these issues effectively, we implemented an additional step to refine further the results from the data provided by the DLC model. We integrated the use of YOLOv5 (Jocher et al., 2022) to generate bounding boxes around the dogs. This technique allowed us to normalize the dogs' coordinates within the footage, ensuring a more consistent and accurate analysis of their movements despite the unpredictable experimental conditions.

In instances where our object detection process resulted in multiple bounding boxes within the same video or frame, we implemented an additional step to ensure accurate tracking of the dog. By calculating the center point of each bounding box and comparing it with the centroid of markers identified by DeepLabCut, we were able to accurately pair each set of markers with the nearest bounding box center. This method effectively addressed the challenge of multiple detection, ensuring that the analysis remained focused on the correct target by matching markers to the closest center of the bounding box. Figure 3 presents an illustration of the entire procedure for extracting normalized landmarks from a single frame of a video.

This was achieved by determining the relative motion of each joint linked to the landmarks, using the formula below:

$$avg_{j,s} = \frac{1}{2 \cdot seg_{size}} \sum_{i=1}^{seg_{size}} \left(\left| \left(p_{j_x}(i) - p_{j_x}(i-1) \right) \right| + \left| \left(p_{j_y}(i) - p_{j_y}(i-1) \right) \right| \right) \tag{1}$$



a) b)

Fig. 3. a) Original frame from the recorded video. b) Frame after extracting markers, with a bounding box detected and drawn. After extracting and normalizing the landmarks, the subsequent phase involved computing a metric for motion across the video frames.

which calculates the average quantity of relative motion taking into account the normalized distance traveled by a specific joint over successive frames. This is done by taking the x and y coordinates of each of the markers for each time segment. For this study, the segment size seg_{size} was set to 1 second, a duration determined experimentally and given the passive nature of the selected task, abrupt changes within the same second are not anticipated. By measuring this motion metric $avg_{j,s}$ we were able to produce a consistent dataset that reflects how much a dog moves in the abandonment stimuli.

3 Results

We measured the canine movement from the trials carried out by using Equation 1, which allowed us to process and translate the movement of the dog into a comprehensive representation across sub-phases of test. Heat maps were used to represent a minute-by-minute visualization of each dogs' activity throughout the trial, capturing the entirety of the motion across time. By segmenting the trial into discrete one-minute segments ('initial', 'intermediate', and 'final'), we were able to detect patterns of mobility. The heat maps, shown in Figure 4, offer an explainable representation of the processed data, highlighting areas of peak activity (darker color), as well as those that are relatively calm (lighter color).

From results presented by each Trial (Figure 4) it was observed that the dog 'Rufo' had greater mobility during Trial 1, while 'Tory' had this same behavior during Trial 2. On the contrary, several dogs showed little movement during both trials, e.g. 'Jeisu'. Both ascending (e.g. 'Kiara' in Trial 1) and descending (e.g. 'Nala' in Trial 2) movement patterns are also observed. Another pattern observed is to start and finish with higher movement, with a decay of movement in the middle of the trial, e.g. 'Hachika' in Trial 2.

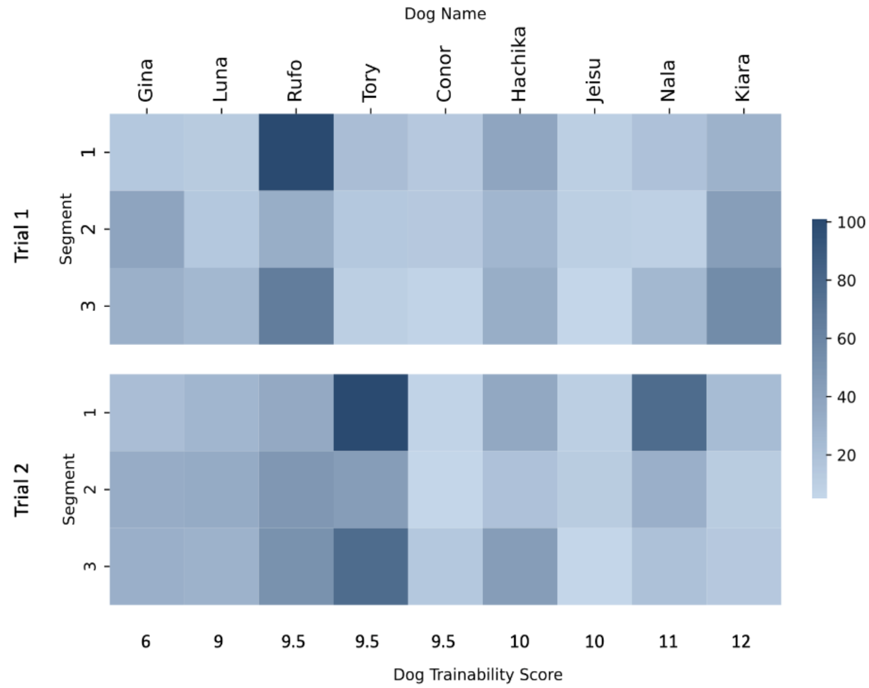


Fig. 4. Average quantity of relative motion (AQRM) for both trials ordered by dog trainability score (Segment codes, 1: initial, 2: intermediate, and 3: final).

It is important to mention that the dogs are presented in ascending order according to dog trainability score, from score 6 for 'Gina' to 12 for 'Kiara'. A slight tendency of less movement (less color) towards the right of the heat maps can be noticed.

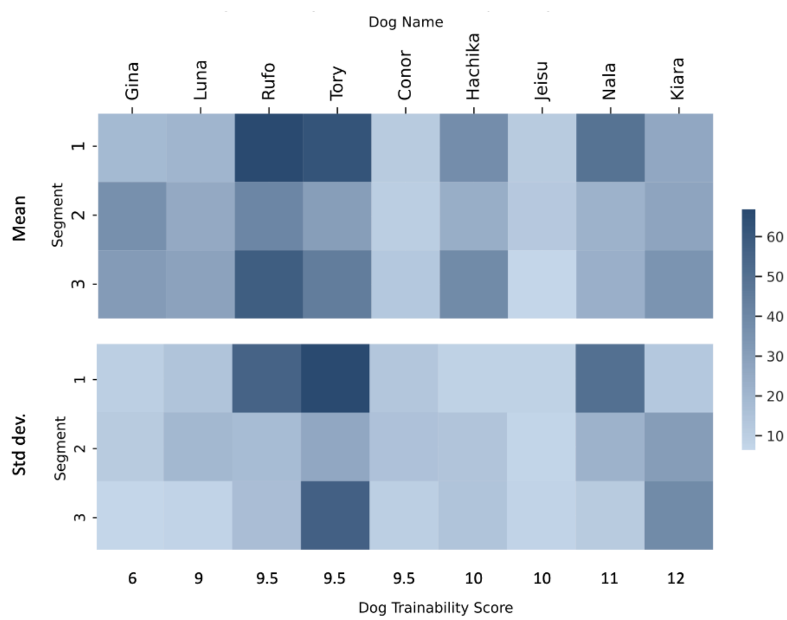


Fig. 5. Mean and standard deviation of AQRM from both trials ordered by dog trainability score (Segment codes, 1: initial, 2: intermediate, and 3: final).

Beyond reporting results for each trial individually, we also examined canine movement by consolidating data from both trials. This analysis was based on a measure of central tendency and a measure of dispersion, as illustrated in Figure 5. Starting by the mean movement of each joint in these two trials as a key statistical measure, as traditional assessments of trainability often overlook inter-trial information that could contain subtle but significant patterns that might otherwise go unnoticed. The mean metric substantiates that ‘Rufo’ and ‘Tory’ exhibit higher motion values, attributed to their elevated activity levels in specific trials. Conversely, ‘Conor’ and ‘Jeisu’ consistently showed the lowest motion values, irrespective of the trial.

To complement the mean movement, we also incorporated the standard deviation in our analysis to capture the variability and consistency of the dogs’ movements. The standard deviation is critical as it illustrates the extent to which each trial’s movements deviate from the mean. This variability can be telling in terms of trainability, as it may hint at a dogs’ adaptability or its potential for stable behavior. Traditional assessments might fail to capture these nuances, as they typically do not quantify fluctuation in a dogs’ performance. In this case, only ‘Tory’ demonstrates a significant behavioral shift across the two trials, whereas ‘Gina’ and ‘Jeisu’ maintain a better consistent behavior between trials.

Finally, the difference in movement between the first and the second trial was also calculated to understand the temporal effects and potential training impact on the dogs, see Figure 6. This difference metric identified changes in the dogs’ behavior from one trial to the next, which can be indicative of learning, habituation, or fatigue. Reporting these differences aggregates an additional angle that we can utilize to understand the evolution of a dogs’ behavior, as well as the effectiveness of the stimuli used in the trials. In this instance, the magnitude of motion may be represented by negative values if a dog increased its movement in the second trial, for example, ‘Tory’. Conversely, higher positive values correspond to diminished activity in the second trial, as observed with ‘Kiara’, or to a lesser degree, ‘Rufo’.

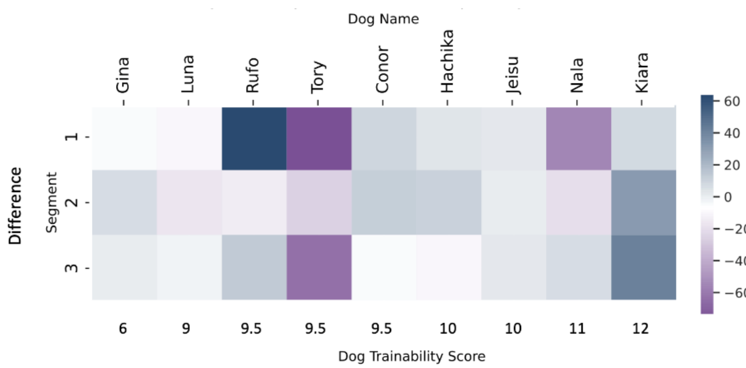


Fig. 6. Difference *(Trial 1 - Trial 2)* of AQRM ordered by dog trainability score (Segment codes, 1: initial, 2: intermediate, and 3: final).

3.1 Assessing the correlation between canine movement and trainability score

In order to find a relationship between trainability and the amount of relative motion, we now present a series of plots that make a direct comparison between a dogs’ trainability score and their relative motion as captured in our trials. This aims to visualize the potential correlations between the recordings of the stimuli and the qualitative assessments done by professionals for each dogs’ trainability.

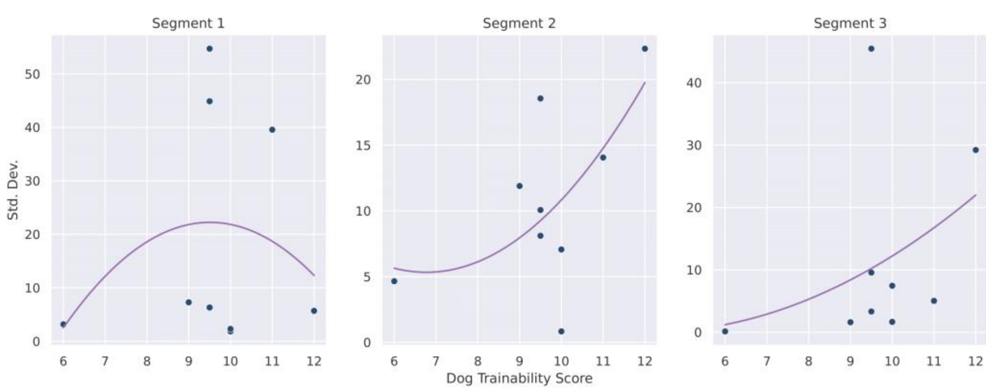


Fig. 7. Standard Deviation of AQRM vs Dog Trainability Score for the mean of each of the three segments of the trials.

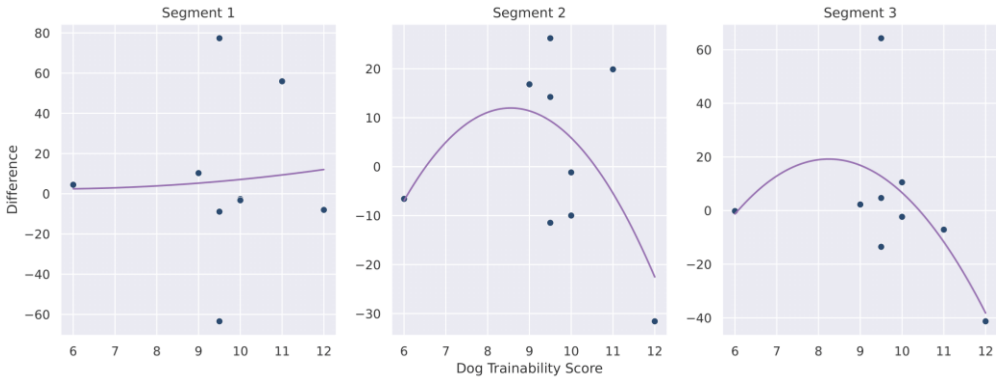


Fig. 8. Difference (*Trial 1 – Trial 2)* vs Dog Trainability Score for each mean of the three segments of the trials.

The standard deviation and difference serve as our primary indicators, as the offer a broader perspective on each dogs' behavior: one that focuses seeks to showcase the consistency of the movement across trials, and another that accounts for the change in movement across them, as shown in figures 7 and 8. These plots also highlight the differences in movement between trials, providing additional insight into the dogs' learning and adaptation over time, something that we also covered by calculating the difference in movement between the trials. Remembering that the scope of this analysis is constrained by the availability of a small dataset, limiting the potential to identify stronger correlations.
From Figure 7, intermediate (Pearson's correlation coefficient, $r=0.54$) and final ($r = 0.36$) segments exhibit a subtle trend indicating that an increase in standard deviation corresponds to a higher trainability score. However, the first ($r = 0.15$) segment displays an opposite trend, with only one sample being an exception (very low std dev and trainability score). This latter pattern is replicated in the intermediate and final segments when considering the difference in movement between trials, yielding correlation coefficients of $r = -0.17$ and $r = -0.31$, respectively.

3.1 Case studies in movement patterns

a) b) c)

Fig. 9. Differences in dogs' behavior across the stimuli. a) Increasing movement in Kiara's 2nd trial. b) Decreased movement in Nala's second trial. c) Uniformly calm movement across Jeisu's first trial.

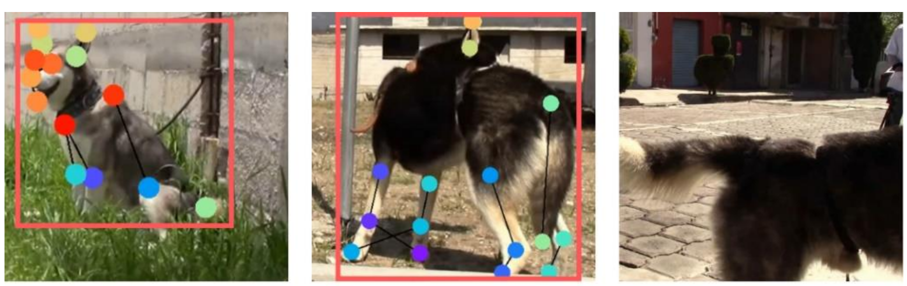
As highlighted earlier, distinct movement patterns emerged during the individual trials for various dogs, offering insight into behavioral tendencies that may affect trainability, see Figure 4. For example, Kiara's first trial exhibits an increase in motion as the trial develops, which is shown in Subfigure 9a. This might suggest an increase in discomfort with the environment as the trial progresses. In contrast, Nala presents a contrast to a decrease in activity during her second trial, shown in Subfigure 9b. This reduction could hint at the dog sitting for the remainder of the trial, displaying calmness, learning from the first trial, or a general decrease in interest. Jeisu's first trial also displays a somewhat interesting pattern: complete calmness throughout the whole duration of the trial, as seen in Subfigure 9c. These individual cases serve as focal points for our study, although there is no direct relationship with the trainability score from this stimulus alone. Each case covers a behavior that may be general when scaling this study to different breeds or stimuli, offering insights into the factors that may affect a dogs' behavior through the latter.

3.2 Limitations of our study

In the task of analyzing canine movement through 2D video in such a naturalistic manner, we confronted several challenges that represented unique obstacles to data integrity and model performance. These cases illustrate the breadth of real-world variables that can impact the application of ML techniques in behavioral analysis.

First, we faced natural obstructions that compromised the precision of our tracking model. As dogs navigated their everyday surroundings, routine obstructions, such as posts or grass, often obscured the sight of some of the markers, especially in the lower parts of the dog. This led to inconsistent tracking, but also resulted in smaller bounding boxes, which tended to under-represent the actual scope of the dogs' movements. The corresponding Subfigure 10a illustrates how these occlusions affected the visibility and the subsequent analysis of the movement data.

Our second case highlights the limitations of machine learning models in the context of considerable diversity among subjects and environments. Despite the application of training techniques with data augmentation, the model exhibited expected failures when faced with the unique combinations of ten different dogs, each with its own distinct environmental conditions, coat color, size, and even husky breed variation. This complexity was further demonstrated by the sheer volume of data, with 18 videos comprising around 1800 frames each. Considering that the model was trained and refined on a dataset of just over 300 frames, this only represented 1% of the total amount of frames, thus the challenge for a good model becomes evident. In order to account for this, we employed methods to extract the best representative of a second (this being the frame with the highest average likelihood). Subfigure 10b depicts an instance where the model crossed the markers of the paws, illustrating the difficulty of creating a one-size-fits-all model for such varied data.



a) b) c)

Fig. 10. Showcased problems when processing data: a) Natural occlusion affecting the detection of markers/bounding box. b) Crossed detected markers for the dogs' paw. c) The dog goes out of frame.

Our third case also deals with the challenges of capturing behavior in an uncontrolled naturalistic environment. The unrestrained setting observes authentic behavior and introduces variables that impact the performance of both our tracking tools. Instances where the dogs moved out of the camera frame required on-the-fly camera adjustments, which were not instant. These events, although infrequent, had a noticeable effect on the integrity of the data and the overall performance of the tracking models. Subfigure 10c shows how both models fail as the dog leaves the frame, making it impossible for the DLC to detect the markers confidently and also draw a bounding box over the dog.

We also visually verify very special cases of dogs' behavior. In particular, an incident deserves mention where a dog ('Luna' in the first trial) was tethered too closely to a tree trunk with its leash, causing discomfort during the initial part of the trial, resulting in a prolonged restraint in its movement. The dog in question ended up sitting after a series of movements that led to adjustment and a better position. Nevertheless, our approach successfully quantified movement throughout this subphase, unaffected by the atypical behavior during the trial.

In a further inspection of the results displayed in Figure 4, which delineates the AQRM for both trials, we can note that there is no evident pattern that directly ties the dogs' trainability scores to their levels of activity; each dog exhibits a unique motion profile or pattern. This was expected, due to the lack of nuanced information that this insight offers. This creates a challenge for further analysis using the rest of the metrics obtained as results.

After analyzing Figures 5 and 7, it is apparent that the relationship between a dogs' trainability and its movement is not straightforwardly discernible from the data. The absence of a clear-cut correlation in the average movement across trials might seem like there are layers of complexity that affect canine behavior. When comparing to a traditional assessment, we found that not only movement is perceived for a trainability score, but also actions that the dog performed in such trial, and these might manifest in different kinds of information not taken into consideration here, such as vocal cues like whining and barking, activities such as urinating or standing on hind legs, and even visual poses, including sitting or resting.

Regarding Figure 7, when analyzing all 3 plots, a higher standard deviation in the average amount of relative motion appears to correlate positively with the increase in the trainability score in the second and third segments. As the trial progresses, the second and third segments might indicate that dog behavior begins to stabilize, and a more discernible pattern emerges. This stabilization may reflect an accurate representation of dog habituation (Pullen, Merrill, & Bradshaw, 2012; Maros et al., 2008), as the first segment of the tests shows that there is a disparity that can be attributed to the initial adjustment period of the dog: a perceived negative emotion from its owner leaving, followed by a habituation process to the environment of the trial.

The data presented in the plot on the left of Figure 8 suggest a nuanced beginning to the dogs' interaction with the abandonment stimuli, one that appears to lack a direct correlation with trainability. However, this indicates that the initial response may indeed be atemporal, reflecting a period where the difference in behavior is minimal and not particularly indicative of future trainability, but when it comes to the rest of the segments, a pattern begins to emerge. The decreasing amount of difference observed suggests that the dogs not only react to the stimuli but interact with the environment and its surroundings in a way that evolves. This might not necessarily reflect stress or discomfort, but rather an increase in familiarity and ease with the stimuli, leading to an interpretation of adaptability and learning.

The goal of this work was to analyze the movement of dogs through 2D video recordings, to elucidate the relationship between movement patterns and dog training capacity during an abandonment test. We expected that more trainable dogs would show less movement during the abandonment test; however, we found a pattern associated with time.

4 Conclusions

In concluding this study, the proposed approach facilitated the measurement of canine movement during tests in real settings, showing resilience to challenges posed by occlusions. Furthermore, a strategy for analyzing movement in subphases was introduced and assessed, enabling the identification of specific behavioral patterns. Conversely, it is critical to reflect on the divergence between our initial expectations and the actual results. Our findings did not consistently substantiate the expectation that motion activity would directly correlate with higher trainability. Instead, we observed that other measures that rise from the statistical analysis of the data, provide a more nuanced indication of trainability.

Looking forward, the path is paved with numerous opportunities for further research. Future work could explore the integration of additional behavioral metrics, such as heart rate variability or temperature, to provide a more comprehensive picture of a dogs' response to training stimuli. Furthermore, additional studies could examine even more intricate visual information, such as activities performed by the dog during the trial, as well as poses, accommodating a wider array of characteristics or environmental variables.

This experiment embarked on an ambitious journey to decode the complexities of canine movement and its relation to trainability through the lens of machine learning techniques, as well as computer vision. By strictly applying these to naturalistic data, we have challenged traditional notions of trainability measurement and assessment. Our findings have painted a picture that is as intricate as it is insightful, revealing that the essence of trainability may lie in the variability and adaptability of behavior, rather than the inconsistent repetition of movement or subtlety in it. As we reflect on the collective insights generated from this study, we are reminded of the complexity of canine cognition and behavior, which continues to unravel in surprising and intricate ways.

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