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Expressive Path Shape (Swagger): Simple Features that Illustrate a Robot's Attitude toward its Goal in Real Time*

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Abstract— **Expressive motion can situate a robot's attitude in its task motions, illustrating real-time reactions. Inspired by acting movement training, we construct path shape features that layer expression into a mobile robot's motion traversal. Our video-study results show that simple variations of path shape and orientation can influence human perceptions of a robot's task, focus, and confidence. We further find that sequencing path features is a useful way to create expressions that are pinpointed in time without requiring changes in velocity. Our quantitative features represent the *Laban Space Effort*: using path shape and orientation along the path to communicate the *direct* or *indirect* attitude of the robot toward its target destination (acting vocabulary italicized). These features illustrate expressive or stylistic aspects of the robot's inner state, filling a gap in the pre-existing literature that has mostly focused on task legibility. Our future work will evaluate temporal and spatial robot motion features in explicit interaction contexts.**

I. INTRODUCTION

Motion plays an important role in human-human communication. As this paper will demonstrate, the way a mobile robot traverses space appears to effect similarly important attributions even with simple degrees of freedom (a single omni-directional base). For example, we find that robot path shape clearly influences attributions toward the robot (e.g., confidence, confusion), and that transitions provide highly salient contrasts as regards the robot's detection of its goal.

We seek to layer such expressive motions into a robot's task actions by varying its trajectory between known start and stop positions. Our path shape features are principled (building on the Laban Effort System), simple (they apply to simple mobile robot motions) and mathematically grounded. In fact, we seek to operationalize the Laban Space Effort, a concept from dance and acting training that qualitatively describes how an agent can use motion to express its attitude toward a goal. Specifically, we explore the impact of **path shape** and **orientation along path** on participant interpretations of a mobile robot's Laban Space setting during a motion traversal (Fig. 1.

To evaluate these Laban Space features, we create videos in which the robot approaches a beverage stand across various path conditions (Fig. 1). As displayed, the robot's paths are composed of sinusoidal (indirect) and linear (direct) path segments. Because our path calculations occur relative to an attentional goal – which we define as an object or location that requires the robot's sustained concentration (e.g., as part of a task) – the motion and orientation parameters are calculated relative to that focal point.

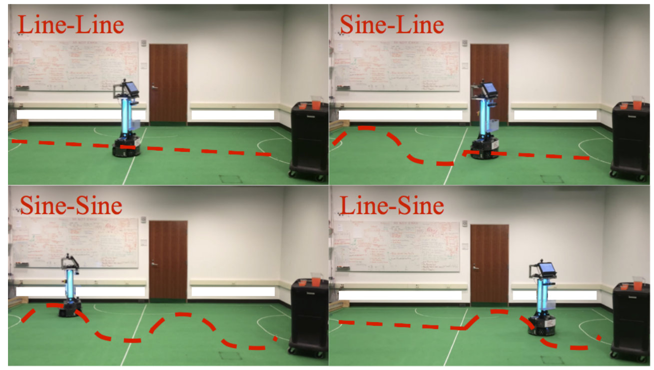

Fig. 1. Compound path conditions with sample attributions: Line-Line takes a linear path to the beverage stand and seems normal / direct; Sine-Line may have been looking for something then found it; Sine-Sine could be confused, playful or weaving around something; Line-Sine may have lost localization, changed mind or lost confidence.

The results confirm that viewers can interpret expression layered on top of a robot's task motions. The parallels in human behavior help clarify our findings. If a person at a music festival cannot make up their mind about what kind of food they would like to eat, they might take an indirect path. But if they suddenly see something on the menu they love, that indirect path could immediately become direct, illustrating their change in state. Alternately, a slight wavering in their path could betray an inherent shyness or ambivalence about their choice.

II. COMMUNICATING WITH MOTION

Research into point-light supports the ability of people to infer emotion from low degree of freedom representations, e.g., human dancing motions [1], and arm motions while drinking from a glass, or knocking on a door [2]. It turns out as long as even simple forms move with or toward a legible goal, we will make attributions about their mental state, task, or social relationships [3] [4] [5] [6]. Further work as found that sequences of motions of abstract objects lead us to create complex storytelling, as found in the well-known "Do Triangles Play Tricks?" study [7], and a single-axis door that one subject thought to have judged him before closing in his face [8].

This work is part of a larger project operationalizing the Laban Effort System to simple robot motions [9] [10]. Our

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use of Laban Efforts builds on previous work in robotics and computer vision that attempt to operationalize this system [11] [12] [13] [14], defining characteristics relevant to simple mobile robots. Past work has shown the value of a designing motion expressions with experts. Willow Garage hired a Pixar animator to convey that the robot was calculating a path, enacting a grasp, or reacting to success or failure [15]. This helped human colleagues sympathize with its efforts, reducing annoyance. Other researchers have focused on task legibility: showing that manipulator path shape enables observers to predict the object for which a robot is reaching [16].

We seek to leverage the benefits of both, taking operationalizing a system from acting to repeatably layer expression on a pre-existing robot task. We do this by leveraging the Laban Effort System. Dancers and actors use the Laban Effort System to represent the full space of expressive possibility for how to perform action, e.g., moving from A to B in a manner that is unenthusiastic [17]. There are four main Laban Effort Vectors within this system, Space, Time, Weight, and Flow. The Efforts form a subset of Labanotation (created in 1963 to record human motions) that codifies the expressive characteristics overlaying a particular motion goal. While past research in robot motion has explored expressive motion features [18] [19], this work builds on the more than 70 years of experience from another field.

III. THE LABAN SPACE EFFORT

This study concentrates on the Laban Space vector, which runs along a scale of Direct to Indirect (Fig. 2) and is meant to represent an agents attitude toward goal [17]. In Laban terms, Direct motion is single focus, whereas Indirect has multiple foci.

To evaluate these Laban Space features, we create videos in which the robot approaches a beverage stand across various path conditions (depicted in Fig. 1). The robot's paths are composed of sinusoidal (indirect) and linear (direct) path segments. Because our path calculations occur relative to an attentional goal, which we define as an object or location that requires the robot's sustained concentration (e.g., as part of a task), the motion and orientation parameters are calculated relative to that focal point. We create videos spanning all possible compound path instances (4 paths) and orientation conditions (2 orientation settings). Our series of online studies collects data that would have been logistically prohibitive to collect in person. We will describe the survey questions at the beginning of each results subsection.

IV. SPACE EFFORT PATH FEATURES

This study concentrates on the Laban Space Effort, which runs along a scale of Direct to Indirect (Fig. 2) and is meant to represent an agent's "attitude toward a goal" (Chapter 2). In Laban terms, direct motion is single focus, whereas indirect has multiple foci. We explore two classes of features to represent the Laban Space Effort: Path Shape and Orientation Setting (Table I).

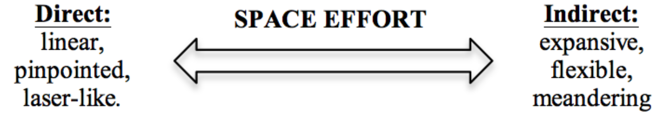

Fig. 2. Illustration of the Laban Space Effort, as described qualitatively in dance and acting training

Path shape represents the linear or sinusoidal motion from A to B, which we parametrize by sinusoidal frequency and amplitude. At the extreme, we expected linear paths to be seen as direct and sinusoidal paths to be seen as indirect, however, we were unsure how the sense of direct to indirect would scale as frequency and amplitude varied (and explore amplitude also in this experiment).

Orientation setting represents the robot's gaze angle during its traversal, either along the path it is traveling, or toward its final goal. We expected that the robot looking at the goal throughout the path would be seen as more direct than the one that was looking along its path (except in the linear path condition). We were unsure, however, what the relative importance would be of the path shape versus orientation setting, and what kind of interaction effect they might have. For example, we thought orientation setting might emphasize or de-emphasize path shape.

TABLE I

SPACE EFFORT (DIRECT/INDIRECT) TRANSLATIONAL FEATURES

Sinusoidal Frequency	Number of periods of the sine, specified in multiples of 0.5, to end path on central axis.
Amplitude	Peak distance of the path from the central axis, where LINE is zero amplitude, SINE is non-zero.
Orientation Setting	*Path*: robot orients along the center of the path, *Goal*: Orients toward goal as it travels along path.

V. COBOT MOTION GENERATION

CoBot is an autonomous mobile robot with a four-wheeled omni-directional base. During its everyday operations, the CoBot robots complete a variety of tasks in an office environment, such as meeting and guiding someone to a location, delivering objects and/or messages [20]. During typical hallway motions, the CoBot operates within a corridor of safe travel that is 0.5 meters wide, has a minimum velocity of 0.2 m/s, and a maximum of 1.0 m/s. The robots navigation system also provides constraints that influence our feature implementations.

Fig. 3 illustrates the steps we use to generate the robot's motion trajectory, given a particular Path Shape and Orientation Setting. We calculate our target stopping position $(\mathbf{x_T}, \mathbf{y_T}, \theta_\mathbf{x}\mathbf{y})$ relative to an attentional goal at $(\mathbf{x}, \mathbf{y})$, also using the attentional goal position as in input for our orientation setting during the motion, as described at the end of this section.

To ease feature calculation, we treat the line between our current position and the attentional goal as our $x - axis$. Given the target position, we calculate the path shape characteristics we would like to use to achieve that target. We do this by choosing a set number of waypoints $(\mathbf{N})$.

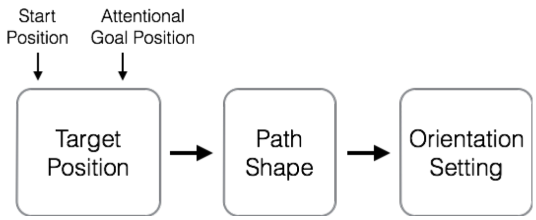

Fig. 3. Flow diagram of the Attentional Goal trajectory calculations

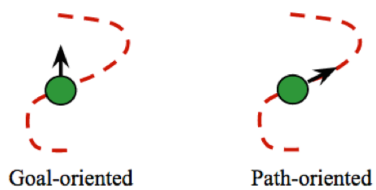

Fig. 4. Illustrations of Goal and Path orientation settings.

Given the start position $\mathbf{x_0}$, the robot's net motion travels along this X-axis, with side-to-side oscillation ($\mathbf{y}$), according to the following equations:

$$\begin{aligned} x &= x_0 + velocity * timestamp \\ y &= amplitude * sine(frequency * timestamp) \end{aligned} \quad (1)$$

The CoBots navigate using waypoints, each thinking it has achieved a waypoint if it comes within a threshold of the desired position ($\mathbf{d}$=0.2 meters). Thus, we calculate the total number of possible waypoints ($\mathbf{N}$) by dividing the total distance along the central axis ($\mathbf{D}$) by the controller resolution ($\mathbf{N} = \mathbf{D}/\mathbf{d}$), with a maximum time spacing of $\mathbf{d}/\mathbf{vel}$. We sample the above equations using the waypoint increment, providing the $(\mathbf{x}, \mathbf{y})$ position commands for each waypoint in the path. The robots have omnidirectional bases, thus making their orientation independently controllable from its path. Thus, the final step is to calculate the robot's orientation ($\theta_\mathbf{N}$) at each waypoint consistent with the overall path orientation setting.

We illustrate the orientation settings in Fig. 4. In the *goal orientation*, the robot orients toward the goal location throughout its motion. In *path orientation*, the robot orients along the direction of the path (subtracting the next location from the current) throughout its motion. At the final waypoint ($\mathbf{n} = \mathbf{N}$), the orientation is toward the goal.

At each previous waypoint (from $\mathbf{1}$ to $\mathbf{N-1}$), we calculate orientation from the following equations:

$$\theta_n = \begin{cases} \tan(\frac{Goal_y - Y_n}{Goal_x - X_n}), & \text{if } goal \\ tan(\frac{Y_{n+1} - Y_n}{X_{n+1} - X_n}), & \text{if } path \end{cases} \quad (2)$$

Goal orientation evokes naturally from a focus on the attentional goal, while we hypothesize that Path orientation could make the path shape more legible and/or seem to be more indirect, as if the robot is focused on its navigation rather than its attentional goal.

In practice, the robot motions occur in the coordinate system of the building map, so we must transform our calculations back into the global coordinate system. In addition, to enact these various paths we must ensure two things: that the approach path is possible given the map (so the robot does not get stuck), and finally, that the approach path is safe, i.e., that the vector of motion for each step is in the sensor range of the robot (so the robot is able to detect unexpected obstacles it might collide into).

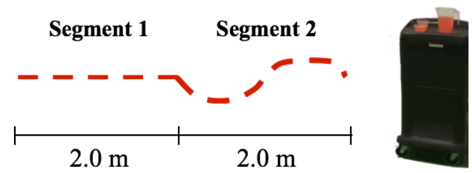

Fig. 5. The robot follows a compound path to the goal

VI. ONLINE EVALUATION

Our research goal is to find out how varying a mobile robot's approach path might change attributions people make about a robot's inner state (e.g., attitude toward the object of its attention). To test this concept, our study evaluates various approach paths of the robot moving toward a beverage stand, as service robots are a common target application for socially interactive robots. We evaluate the impact of path-shape changes by creating paths with two segments, as in Fig. 1, and vary oscillation amplitudes.

Our study setup includes two consecutive path segments, as depicted in Fig. 5. Each segment length is 2.0 meters and includes a full period sine wave. The end distance is 0.3 meters, end angle is 0 radians (facing stand), and overall velocity along X is 0.5 meters/second for all paths. Note that having two sequential sinusoidal segments of the same amplitude merely results in two periods of that sine wave.

We select three sine amplitudes from the corridor of safe robot motion we currently use in the hallways on campus: 0.5 meters, 0.25 meters and 0 meters (Table II), which we label, SINE, $\frac{1}{2}$SINE, and LINE, respectively. This is a conservative range, as the hallways are closer to 1.5 meters wide, but people occasionally leave objects by the wall outside their doors.

TABLE II

PATH AMPLITUDE FEATURE: CALIBRATION CONDITIONS

Label	Amplitude	Frequency	X-Velocity
SINE	0.5 m	0.5 cycles/m	0.5 m/s
$\frac{1}{2}$SINE	0.25 m	0.5 cycles/m	0.5 m/s
LINE	0 m	0 cycles/m	0.5 m/s

The variables left to us for manipulation are segment sequence, sinusoidal amplitude and orientation condition, as in Table II. We ran several online studies, including two permutations of Segment1+Segment2 path shapes (A1,A2). Our online study questions compare the basic compound paths (A1 analyses) or assessments across sinusoidal amplitudes (A2 analyses). We also evaluate constant orientation settings only, as orientation settings are equivalent in linear path segments.

TABLE III

EXPERIMENTAL VARIABLES BY ANALYSIS

A1. Compound-Paths

SINE-SINE	SINE-LINE	LINE-SINE	LINE-LINE

A2. Varied Sinusoidal Amplitude*

SINE-SINE	$\frac{1}{2}$SINE-$\frac{1}{2}$SINE	LINE-LINE

*$\frac{1}{2}$SINE has half the amplitude of SINE

B. Orientation Conditions

GOAL	PATH

We created seven videos of the A1 compound paths to include both orientation conditions (LINE-LINE goal and path orientations are equivalent), and two additional videos of $\frac{1}{2}$SINE-$\frac{1}{2}$SINE, across both orientation conditions. We spend the most time on the seven extremal compound paths (i.e., those composed of SINE and LINE segments), using the three baseline paths analyses (by which we mean there is no path shape change), to explore whether attributions scale with sinusoidal amplitude.

We ran a variety of surveys on Amazon Mechanical Turk, including open-ended questions, Likert scale questions (multiple choice answers ranging from Agree to Disagree) and Semantic differential scales (anchored by opposing concepts like Very Indirect and Very Direct). The large subject population there gave us the opportunity to measure various independent features and explore a range of qualitative and quantitative analysis methodologies, which would have been logistically prohibitive in an in-person study.

Across our open-ended questions and quantitative analyses (comprising 6 total surveys), we had 252 unique users who contributed 688 responses. We treat this as a between subjects experiment, collecting 10-20 independent video labels per condition, depending on the analysis, and prohibiting workers from labeling the same video more than once. To constrain our subjects to a single set of cultural norms, we required that participants be from the United States.

VII. RESULTS I: QUALITATIVE

The goal of collecting data from people was to characterize the way they interpret the robot motion. We begin with the open-ended questions, which provide insight into how people interpreted our motion features. We also use these responses to seed survey questions later. Our first question asks them to describe what is happening in the video. The second asks them to provide three adjectives describing the robot's path. The third question explicitly tells viewers that the robot is approaching a beverage stand, and asks them to explain the presence of a transition point in the SINE-LINE and LINE-SINE paths only.

Subject Descriptions of Robot's Motion

To validate our study setup (that the story of the robot approaching the beverage stand was clear irrespective of path features), we had 85 subjects watch all possible compound paths without priming, then asked them:

TABLE IV

SUBJECT INTERPRETATIONS OF MOTION SEQUENCE

Approaching stand	54
Moving/functional	20
Inner state	5
Alternate task	6

Question 1: "Describe what you think is happening in the video."

People were largely task-oriented in their descriptions (Table IV). Fifty-four (64%) subjects mention the beverage or stand as the object of the robot's motion and (24%) describe the robot's motion directly, e.g., "The robot is crossing the room." Only five subjects describe aspects of the robot's inner state, e.g., "Robot is moving as though it is unsure," probably because of the procedural question. Six reference unrelated tasks such as playing soccer, moving a podium or vacuuming, perhaps in jest.

These descriptions occurred regardless of which path shapes were assigned to the first and second segments, thus, it appears that the robot's task comes through irrespective of path. Given the open-ended nature of the question, we also find it likely that more people understood the beverage stand to be the object of the robot's motion. This is good, because you will remember that the system goal is to layer expression onto a robot task, not replace the task.

Just in case, in the remaining analyses, we tell people explicitly: "In the video linked below, a robot approaches a beverage stand."

Subject Attributions to Consistent Path Shapes

In our next analysis we seek to gain information about people's attributions toward the basic SINE and LINE path shapes across orientations. In an open-ended question, we asked subjects to:

Question 2: "Provide three adjectives that describe the robot's motion."

We assigned 45 subjects at random to one of the compound shape conditions. To visualize the response, we provide word-maps of the adjective data (Fig. 6), in which word frequency maps to word size and low-instance words are chosen at random to fill out the graphic (tagcrowd.com). Note that during the LINE segments, the two orientation settings are equivalent. All path types were called 'smooth' and 'slow,' but as you can see in Fig. 6, people seem to easily distinguish the linear from the sinusoidal pathways.

Sinusoidal motion with differing orientation settings produced subtly different word maps. When the robot is looking along the direction of motion (path orientation), additional words include 'searching' and 'explorative.' When it looks toward the beverage stand (goal orientation), additional words include 'hesitant' and 'uncertain.' Perhaps side-to-side motion with goal-orientation can create a back channel

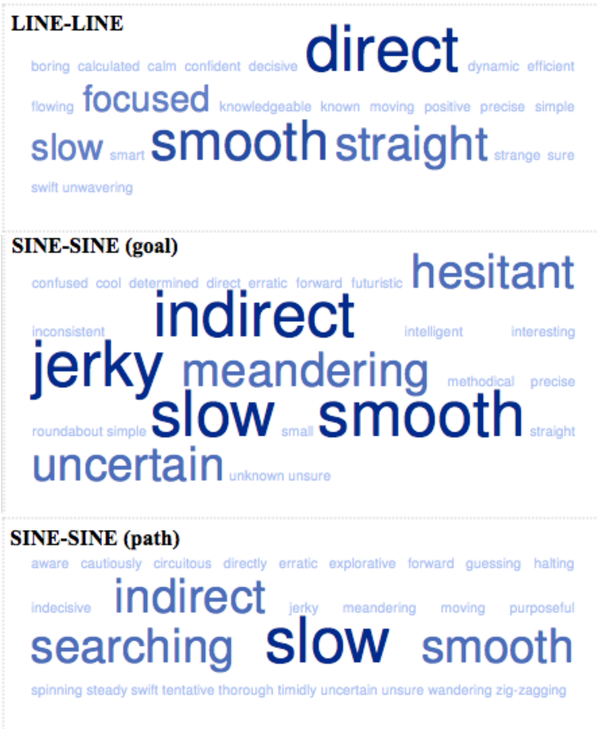

Fig. 6. Word-maps of adjectives subjects used to describe paths: 1) LINE, 2) SINE while facing goal, and, 3) SINE while looking along the path.

indicating second thoughts about achieving its known goal. In all cases the descriptions indicate that people interpret varied path shape and orientation qualities as communicating aspects of the robot's internal or task state.

Subject Interpretation of Path Shape Changes

Our final question involved understanding how subjects interpret changes in the robot's motion style, e.g., when the motion setting goes from indirect to direct or visa-versa. We provided subjects with videos of SINE-LINE and LINE-SINE paths only (both orientation conditions), and made the following request:

Question 3: "Describe what is happening in the video. Why is there a transition point?"

Table V provides representative samples of the 36 replies. In these responses, we see explanations of:

- SINE-LINE as scanning, exploring or correcting,
- LINE-SINE as erratic, cautious, careful

It is interesting to note that there were two instances in goal orientation where subjects did not notice a transition point, probably because the constant speed toward the goal and goal orientation made for a smooth transition between path shapes. We will refer back to these responses as we interpret our numerical results in the following subsection.

VIII. Results II: Quantitative

In this subsection, we review our three quantitative surveys. First, we assess how well our chosen path shapes map back to Laban Space concepts of direct and indirect. Second, we assess the impact of path shape on people's impression of when the robot had become aware of the goal. Thirdly, we quantify the inner state attributions people make about the robot's compound path motions, using adjectives from the qualitative responses.

TABLE V

Subject Interpretations of the Transition Point

SINE-LINE
"It seems that the robot is first scanning the area before ascertaining that the beverage stand is its sole target." (path) "The robot is exploring the room during the first half of its path." (path) "The robot goes the wrong way, then corrects itself." (path) "The transition point happened because the robot finally got its positioning in line with stand" (goal) "The robot is exploring the room. That is why it is taking an indirect path to the stand." (goal)
LINE-SINE
"A robot moves across a room towards a beverage stand...but the robot seems to move sort of erratically and does not go directly there." (path) "A robot starts toward the beverage stand. The robot can't move diagonally so he has to come forward and then turn to reach the beverage stand." (path) "The robot is moving directly during the first half of its path. At that point it becomes cautious; that is why it then takes an indirect path to the stand." (goal) "The robot makes its way slowly, carefully changing its direction as if it had a sensor, until it reaches its destination" (goal)

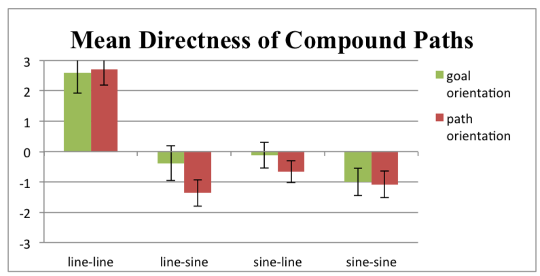

Fig. 7. Mean Directness, N=86 (-3=Very Indirect, 3=Very Direct), Note that line-line orientations should result in equivalent behaviors.

Space Effort Results: Direct/Indirect Legibility

The inspiration for our initial work comes from the Space Effort, thus the first analysis of compound paths is to evaluate whether people indeed found LINE to be direct and SINE indirect. We use a 7-point semantic differential scale (-3=Very Indirect, +3= Very Direct) to answer:

Survey 1: "How would you describe the robot's motion?"

Fig. 7 shows linear paths are strongly associated with Very Direct labels and sinusoidal paths with Somewhat Indirect labels, regardless of orientation setting. These values were what we had hoped for; the sinusoidal paths are seen as approaching a goal overall, but taking an indirect path to get there.

Statistically, when we run a 3-way ANOVA to evaluate whether segment1, segment2 and/or orientation setting can predict subject directness ratings, we find a main effect from both segments (in other words they are statistically significant predictors of subject directness labels) and a trend from orientation (segment1 $p \leq .0001$ F(1, 21.3), segment2 $p \leq .0001$ F(1, 35.9)). Segment2 has an even higher F-value than segment1, so you might infer that the final value of the path is most important in rating Directness. While orientation appears to play a role when there are path shape changes in Fig.7 with the goal orientation being read as more neutral, and the path orientation for both being read as more indirect, statistically, orientation does not predict directness ratings.

We also find a strong interaction effect between segment1 and segment2 ($p \leq .0001$, F(1,17.1)). An interesting observation is that the path orientation of LINE-SINE is rated to be the most indirect of all compound paths, while the SINE-LINE goal path is rated to be neutral. So, a robot that approaches its target then veers away is being actively indirect, whereas a robot that has an unclear goal that becomes clear might have been trying to be direct the whole time. As has been previously shown in the section 5.2.5 open-ended question results, people apply storytelling to the sequences of movement, which is probably the explanation for these heightened ratings.

Space Effort Results: Goal Knowledge

In this section, we assess whether compound paths impact people's reading of when the robot has detected or acquired information about its goal. We asked participants to watch their assigned video and answer the following question:

> *Survey 2: "When do you think the robot acquires knowledge of the goal?"*
> *A: Before the video begins*
> *B: Toward the start of the path*
> *C: Toward the middle of the path*
> *D: Toward the end of the path*
> *E: Never*

We obtain 86 labels distributed across compound path and orientation conditions. This time, our three-way ANOVA of segment1, segment2 and orientation finds a main effect from segment1 and segment2 and a trend from orientation (segment1 $p \leq .0001$ F(1, 18.2), segment2 $p \leq .0001$ F(1, 24.9), orientation p=0.095 F(1,2.8)). So orientation influences people's attributions about the robot's relationship with its goal more than people's ratings of the directness of the path. There is also an interaction effect between segments (p=0.0167, F(1,5.98)).

We present our full results in Fig. 8. We again find that segment order matters. SINE-LINE appears to detect the goal toward the middle of the path; it explores, finds its target and proceeds to move in a straight line. People seem confused about LINE-SINE, with a wide distribution of responses that is consistent with the varied qualitative descriptions (Table V).

Almost all subjects label the LINE-LINE path as knowing about the goal before the start of the video. The most common SINE-SINE rating implies the robot discovered the

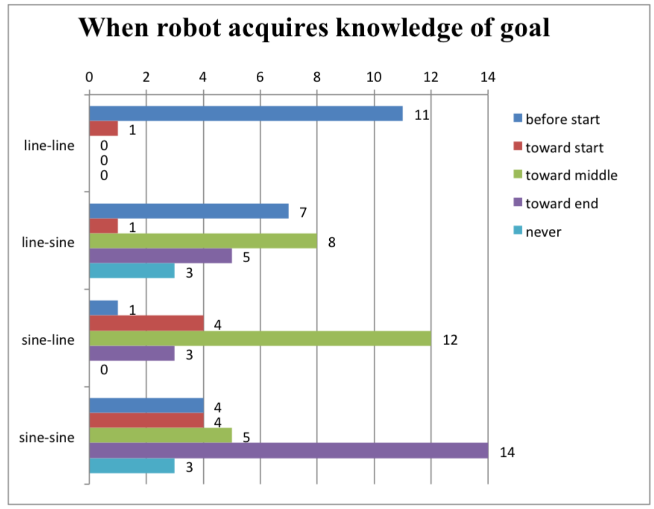

Fig. 8. Counts for when robot acquires knowledge of goal, divided by compound path type, N=86

goal toward the end of the path, i.e., when the robot came in final proximity of the beverage stand and stopped.

The initial linear segment may be why some said 'before the start,' the change may be way others say 'middle,' and the finishing sinusoid may be why the rest choose 'toward the end' or 'never.' Note that subjects only choose 'never' in compound paths that end with a SINE.

Space Effort Results: Attributions

Finally, we explore attribution concepts collected in Question 2 (Fig. 6. We asked subjects to respond to the following statements in random order using a 5-point Likert scale, where -2=Disagree, and +2=Agree:

> *Survey 3.1: "The robot's motion is focused."*
> *Survey 3.2: "The robot's motion is hesitant."*
> *Survey 3.3: "The robot's motion is explorative"*

Focused: Subjects have strong feelings about linear segments, seeing them as highly focused. The compound paths containing sinusoids have more subtle responses (Fig. 9). SINE-SINE is rated least focused (all other paths rated somewhat focused). Overall, the focused ratings have a main effect from all three input variables: segment1 p=0.0002 F(1,15.5), segment2 p=0.0024 F(1,10.1), orientation p=0.0127 F(1,8.1). This is the only statistical analysis that does not show an interaction effect between segments.

Explorative: SINE-LINE is rated most explorative – the contrast tells a story. This is supported by the statistical results, in which we again find three main effects: segment1 p=0.0004 F(1,13.9), segment2 p=0.0275 F(1,5.1), orientation p=0.0012 F(1,11.5), but this time also an interaction effect: seg1*seg2 p=0.0018 F(1,10.7).

Hesitant: SINE-LINE is also rated most hesitant. In fact, no other paths had positive hesitance ratings. This time, we find a very high impact of the initial segment and orientation: segment1 p=0.0247 F(1,5.3) and seg1*seg2 p=0.0018 F(1,4.5).

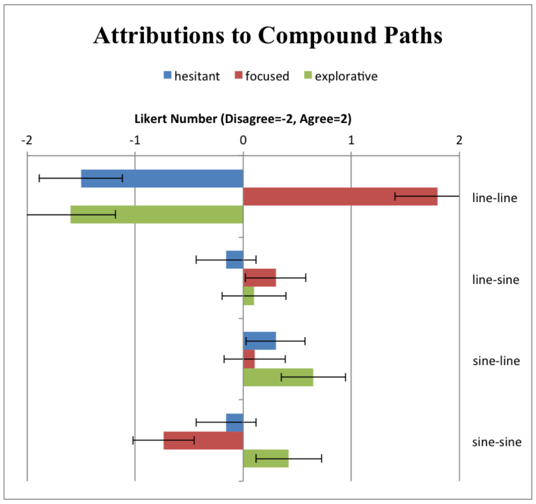

Fig. 9. Attributions to the Compound Paths, $N = \{90, 90, 90\}$

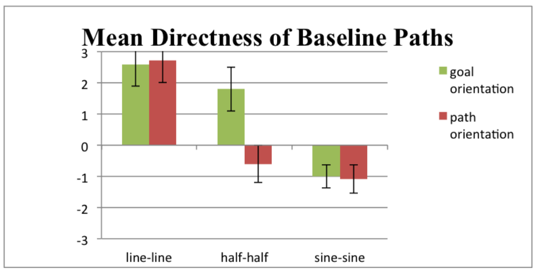

Fig. 10. Mean Directness across Sinusoidal Amplitudes, $N = 52$ (20 half-half)

This result shows the power of storytelling. We had expected that LINE-SINE would be read as hesitant, but perhaps recalibrating to the target or losing functionality (i.e., behaving erratically) was a more dominant interpretation, perhaps thinking of the robot as a machine rather than an agent. The SINE-LINE ratings indicate that the first segment plays a greater role in predicting hesitance (delay before a following action).

IX. FEATURE CALIBRATION

In this section, we briefly analyze how varying sinusoidal amplitude impacts subject directness ratings and attributions. Our hypothesis was that ratings would vary linearly between SINE and LINE. To evaluate this hypothesis, we choose a low amplitude sinusoidal path at half the amplitude of SINE, that we call $\frac{1}{2}$SINE (see definitions in Table II).

Calibrating Directness

We first analyze the impact of lower amplitude sine waves on subject Directness ratings. We present our results in Fig. 11, in which the SINE and LINE data matches up to Fig. 9, but also includes the data from the $\frac{1}{2}$SINE labels. In this case, orientation setting appears to impact people's detection of low-amplitude sinusoidal motion, probably because of the subtlety of the side-to-side motion otherwise.

In goal orientation, people rated the $\frac{1}{2}$SINE similarly to LINE baseline, however, in path orientation, people rated

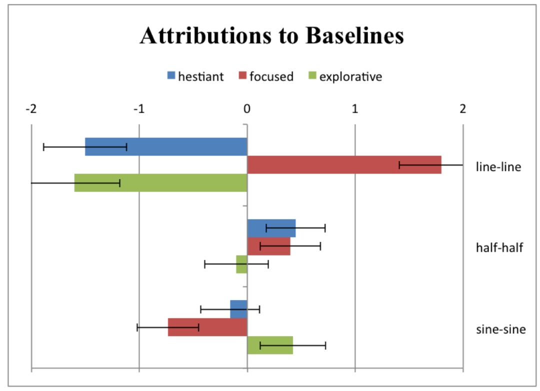

Fig. 11. Mean Attribution by Sinusoidal Amplitude, N={50,50,50} (60 half-half)

$\frac{1}{2}$SINE closer to SINE. Perhaps this new segment $\frac{1}{2}$SINE appears to be more like the natural variation present in human gait, and maintains many of the Directness attributes of a linear segment in goal orientation.

Because of the subtlety of the path motion, it seems that orienting along the path (path orientation) was necessary to reveal the shaping. In a 2-way ANOVA of path-shape and orientation, however, only path-shape showed statistical significance: $p \leq .0001$ F(2,23.5). The directionality of the means, however, suggest that feature calibration will play an important role in assuring the readability of a particular CLE feature.

How Calibration Impacts Attributions

Next, we assess attributions, and how they might vary with changing sinusoidal amplitude. We plot the mean response or the three basic path shapes in Fig. 11. In a 2-way ANOVA of path-shape and orientation, we find a main effect from both path-shape and orientation across all adjectives.

Focused and Explorative appear to vary linearly in the expected directions, consistent with our initial hypothesis. Subjects rated SINE most explorative, and LINE the most focused. In contrast, if we look at the Hesitant mean, we find that $\frac{1}{2}$SINE is rated to be the most hesitant of the baseline paths. This result goes against our initial hypothesis. Apparently, expression does not always vary linearly between sinusoidal extremes. A possible explanation is that lower amplitude oscillation appears to present a backchannel, as if the robot has a subconscious dread of the goal that it is nonetheless approaching.

X. EXPLORATION OF MOTION CONTEXT

Before summarizing our findings, we briefly step back to justify whether this scenario would be relevant in a true restaurant or bar environment. To do so, we conducted an ethnographic interview with a local bartender after demonstrating the robot's motion. We asked him whether these kinds of approach paths resonated with anything he experienced working in a restaurant setting. He said,

> "You can usually tell by the way people walk into the bar how to respond to them. If they're

> looking around and acting unsure of themselves... you offer them a menu... If they walk straight to the bar, making eye-contact the whole way and grab a stool, you ask them if you can take their order, because they probably know exactly what they want to drink."

These descriptions have clear parallels to the indirect and direct Laban Space motion feature (as well as Laban Time, but we'll save that for a future paper). Since the motions we evaluated in our study mapped more to a robot server, however, we also asked about how restaurant co-workers utilized expressive motion and its impact. He said he found it easy to interpret a server's sense of urgency from their approach style:

> "If the restaurant's not busy, the servers will put in an order and chat while it's being made. If it's busy, they rush over, or try to make eye-contact, and you can see them lean against the bar."

He said he would occasionally ask a server if they needed something special if they looked stressed, but that while he was aware of the servers' attitudes toward getting the drinks, he was not aware of changing his working pace because of them. He did say, however, that their approach style impacted his likelihood to socialize with them.

Although this was an interview with a single person, we find it promising that he indicated parallels in interpreting both customer and coworker approach path motions. The interview also helps identify areas for extending this work: human tracking and social bonding.

XI. CONCLUSIONS

The central idea of this paper was to evaluate how people interpret robot attitudes via their motion patterns. We have found that path shape influences peoples attributions toward the robot (e.g., confidence, hurry), and that path shape changes provide contrasts that are particularly salient to people, in particular:

- SINE-LINE path shape changes help illustrate the moment a robot acquires knowledge of its goal; it can also indicate hesitance.
- Linear motion is easiest for people to interpret, with high means in all tests, and positive ratings for focused and direct.
- LINE-SINE path shape changes seem harder for people to interpret, but with goal orientation suggests that the robot is broken or lost track of the goal.
- Calibration is important as changing amplitudes of a feature impacts its legibility.

Given people's rapid ability to interpret robot motion at a glance, the the significant effect of segment ordering, more robot designers can begin to leverage this communication modality in interaction contexts. As suggested by our ethnographic interview, it seems likely that robot motion expressions will be useful for both coordination and camaraderie.

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