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Keep on Dancing: Effects of Expressive Motion Mimicry

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***Abstract*— *Expressive motion* refers to movements that help convey an agent's attitude towards its task or environment. People frequently use expressive motion to indicate internal states such as emotion, confidence, and engagement. Robots can also exhibit expressive motion, and studies have shown that people can legibly interpret such expressive motion. *Mimicry* involves imitating the behaviors of others, and has been shown to increase rapport between people. The research question addressed in this study is how robots mimicking the expressive motion of children affects their interaction with dancing robots. The paper presents our approach to generating and characterizing expressive motion, based on the Laban Efforts System and the results of the study, which provides both significant and suggestive evidence to support that such mimicry has positive effects on the children's behaviors.**

I. Introduction

We are interested in studying how people interact with robots that exhibit *expressive motion* [9-12]. Expressive motion refers to movements that are not directly related to achieving a task, but that help convey an agent's *attitude* towards its task or its environment, such as emotional state, confidence, engagement, etc. Expressive motion in people is an efficient and, typically, effective means of communicating such attitudes. We are particularly interested in expressive motion that is layered on top of task-achieving behaviors, using the same actuators for both expression and task achievement [9].

More specifically, for this paper we are interested in how *mimicry* of expressive motion by robots affects the behavior of people. Mimicry involves the nonconscious "taking on the postures, mannerisms, gestures, and motor movements of other people" [3]. This includes behaviors such as face and hair touching, leg crossing, facial expressions, and affect [3]. Experiments have demonstrated that people tend to like and/or feel more rapport with those who are mimicking them, even if they are not aware that they are being mimicked [26]. Similar results have also been shown to hold with realistic avatars [2].

It is not clear, however, if such results would hold for robots, whose morphologies typically differ from humans. This is especially the case for robots with limited degrees-of-freedom, since they would not be able to realistically mimic motion behaviors of people. On the other hand, it should be possible to mimic the attitudes of people using expressive motion, potentially establishing rapport via shared affect [5]. Thus, we would like to investigate the effects of expressive motion mimicry.

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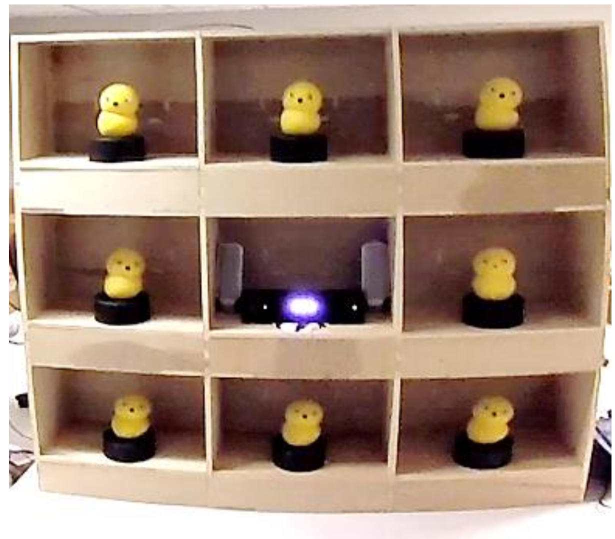

Figure 1. 3x3 grid of eight dancing Keepon robots, with Kinect sensor and stereo speakers in the middle.

Specifically, our research question is whether mimicry of expressive motion affects children's behaviors during the activity of dancing together with a group of robots (Figure 1). Are there differences in behavior when the robots are mimicking the children's expressive motion, and does that indicate something about rapport?

Our approach is to use the *Laban Efforts* to both characterize and generate expressive motion. The Laban Efforts [14] is a framework, developed in the context of dance and theater, that characterizes the *how* of an action – how articulated, forceful, or expansive is the action. Our work and others [10, 11, 16, 24] have demonstrated that the four Efforts – *Time, Space, Weight*, and *Flow* – can be used to enable robots to expressively communicate attitude. Others have used the Laban Efforts to characterize people's behaviors and emotions [6, 16, 22, 27]. We believe, however, that this is the first work that uses a consistent framework for the Effort System to both generate and characterize expressive motion.

For this study, mimicry is achieved by using Kinect data to estimate each of the four Efforts of children as they interact with the robots, and then having the robots respond by exhibiting the same set of Efforts. Note that the robots are not doing the same actions or gestures as the children, but instead are mimicking their expressivity, as determined by their Laban Efforts, as the robots (and children) dance to music.

As an indication of the establishment of rapport between children and robots, our experiment was designed to measure the impact of the robots' mimicry of the children's expressive motions on their behaviors. In particular, we used several quantitative measures, including time of engagement, changes in perceived Efforts per minute, and time spent in each Effort, as indicators of children's interest and/or rapport with the robot. Our hypotheses are:

- H1. Children will engage longer with robots that mimic their expressive motions.
- H2. Children will exhibit more diversity in motions when being mimicked.
- H3. Children will exhibit more "high energy" movement when the robots mimic their expressive motions.

Our study with 45 children indicated that H2 is clearly supported. While H1 and H3 were not supported, there is suggestive evidence for both. In addition, our results show that the song being played as the robots and children interact has a significant effect, as does gender.

II. Background and Related Work

A. Laban Efforts

The Laban Effort System is part of Laban Movement Analysis, which was developed to record dance choreography [8]. It is also used to train actors [12] and has been used to annotate motion in many movement-related fields [13].

The Effort System attempts to relate inner state and attitude to the dynamics of motion characteristics. Laban identified four Efforts – Time, Space, Weight and Flow – that he maintained spanned the space of possible expressions. While the Efforts are a continuous 4-dimensional space, most approaches use only the polar opposite ends of each dimension. Specifically, the Time Effort can be *sustained* or *abrupt*; the Space Effort can be *direct* or *indirect*; the Weight Effort can be *heavy* or *light*; and the Flow Effort can be *bound* or *free* (Figure 2).

Combinations of the efforts can be used to convey different attitudes, for instance, Laban categorized *abrupt, direct, heavy* and *bound* as displaying a "fighting disposition." In this paper, we refer to the combination of *abrupt, indirect, light* and *free* as "high energy" and *sustained, indirect, heavy* and *bound* as "low energy," differentiating Efforts that involve quicker, larger motion from those involving slower, smaller movements.

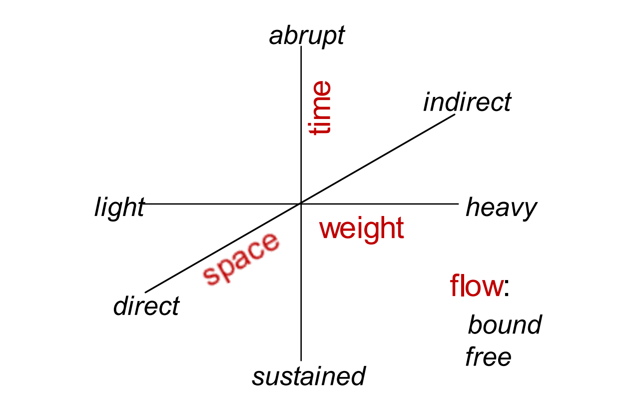

Figure 2. The 4-dimensional Laban Effort system

B. Related Work

Various robotics researchers have singled out the Laban Efforts as a singularly applicable design framework for robot expressive motion [9-15]. Researchers typically use a variety of features for generating expressive motion, including velocity, acceleration, jerk, torque, motion direction, inner angle of joints and the robot head, and peaks in off-axis motion. Some, such as those that calculate the inner angle of the head and each joint [14, 16, 17], are not readily applicable to low degree-of-freedom robots that have no arms. Others utilize acceleration and jerk [9, 17, 19, 20], which can be difficult to distinguish, by themselves, when range of motion is small (our own work has also confirmed that using acceleration is not very transparent for rotational degrees of freedom [9]). In addition, most researchers do not consider all four the Efforts, with Flow being the Effort most often omitted (a notable exception is [23]). Our work is notable because it adapts each of the four Laban Efforts to low degree-of-freedom robots, and it is the first to actively overlay Laban features onto robot tasks [8-12].

Researchers have also used the Laban Effort system to characterize human behavior. Many of these approaches have used relatively simple features that are readily measured. For instance, [6] uses the acceleration of the head, torso, hands and feet (Time Effort) and [22] use simple hand motions (Space Effort) to classify behaviors. Other researchers have used the Efforts as a framework for inferring affective state. Lourens et al. [16] used experts in motion analysis to validate two Laban Effort features. Others have used the Efforts to extract expressive state from human dancers [21, 25]. Zacharatos et al. [27] characterized expressive motion of people playing video games, calculating Time and Space Efforts to estimate concentration, excitement, and frustration. They used hand-labeled data and supervised Machine Learning techniques to train classifiers for such states. As in these other approaches, our own work uses relatively simple temporal and spatial features to characterize the Efforts, often times specialized for the task (dancing) and type of available sensor information (relatively noisy Kinect skeleton data).

This work also derives from earlier research in the effects of rhythmic dance on the behavior of young children [18, 19]. While that work also involved how Keepon robots imitating children would affect their interactions, it imitated only at the rhythmic aspects (beat) of the children's behavior and not the more general expressive motions of the children.

III. Generating Expressive Motion

We have previously developed a consistent framework for representing and combining the Laban Efforts, layering them on top of task-achieving behaviors. This framework, which we term the *Computational Laban Effort (CLE)* system [8], has been applied to several robot morphologies and tasks, and has been validated in terms of legibility of the Laban Efforts that the robots display [9, 11]. The CLE system specifies *features* of motions (velocity, acceleration, timing, range) associated with the Efforts and an algorithm for combining them.

The Keepon robots have four axes (roll, pitch, pan, and compression, Figure 3). The dancing task involves rolling

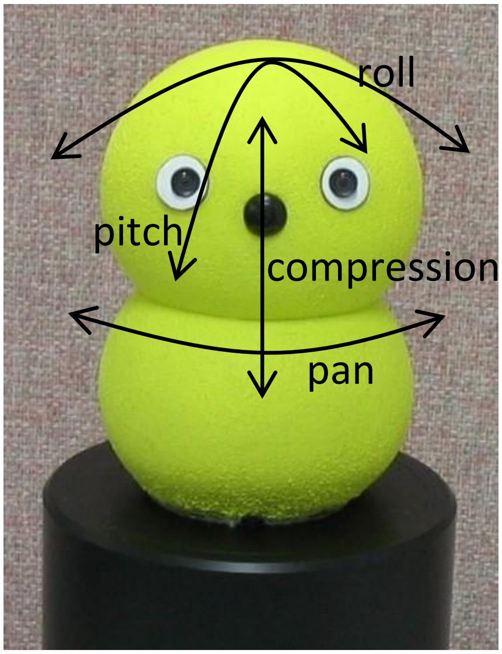

Figure 3. The four axes of the Keepon robot

back and forth in time to the beat of the music, while panning to face different directions, pitching front to back, and compressing up and down. Doing these individual motions with different characteristics defines how the Laban Efforts are displayed as the robots are dancing. The same algorithm is used for calculating the motion of each axis, with some interdependence between the Efforts and some task-specific modifications, as specified below (see also Table 1).

The *Time* Effort conveys an agent's attitude towards time – whether the agent is rushed or relaxed. While **velocity** is an important indicator of temporal attitude, it is an insufficient differentiator for a dancing task, where the goal is to maintain a consistent beat. Fortunately, other attributes that are relevant to the Time Effort, including **acceleration** (how quickly does the motion begin/end) and **arrival time** (early, on time, late), are more applicable to the dancing task. Specifically, for the *sustained* attribute, we simply use the period of the beat; for the *abrupt* attribute, we use 60% of the period. For example, for a song with 120 beats-per-minute, the *sustained* attribute movements take 0.5 seconds, which gets the robot to its reference position, as specified by the Space and Flow Efforts, right on the beat; for the *abrupt* attribute, movements take only 0.3 seconds, arriving before the beat. The robot thus moves faster and then stops and waits for the next beat to begin, thus appearing rushed.

The *Space* Effort conveys an agent's attitude towards its task – whether it is focused, or not. One way to express this is through focus of attention – does the agent look at the object of its task directly? For the interactive dancing task, we interpret this as how closely the robot's **orientation** is facing the participant as it moves during the dance. The skeleton data from the Kinect sensor is used to determine the participant's head position. The pan and pitch angles needed for each robot to look at that position are calculated using straightforward trigonometry, and used as the mean angles μ of the pan and pitch axes. Then, some noise is added to the

Table 1. Features used for the Laban Efforts

Laban Effort	Features for Generation	Features for Characterization
Time	Velocity Acceleration Arrival time *(also influenced by Space and Flow efforts)*	Velocity
Space	Orientation	Orientation Rotational velocity
Weight	Acceleration Height (compression) Bending (pitch) *(also influenced by Time and Flow efforts)*	Acceleration Hand height
Flow	Range of motion	Body extent Body ratio (width/height)

angles based on a variance v. At each beat, the calculated focus angles are simply: μ +/- $rand(v)$, where *rand* chooses uniformly from the argument value. Each axis has its own μ and v. For the *direct* attribute, v is used as given; for *indirect*, 2.5 times v is used. For the roll angle, μ=0; for the pan and pitch axes, μ is the angle needed for the robot to face the participant. For these three axes, v=5°, thus, the *direct* attribute angles vary +/-5° from the base, and the *indirect* attribute angles vary +/-12.5° from the base. For these axes, v was chosen to make the two attributes appear distinctive, while being careful not to exceed the range limits of the axes, especially in concert with the Flow Effort (see below). For the compression axis, μ is determined by the Weight Effort (see below) and v=0 (so there is no variance, which was chosen mainly because the compression axis has a very limited range of motion, so any non-trivial variance would impinge on the range of motion of the compression axis).

The *Weight* Effort conveys a sense of force, either the effect of outside forces acting on the agent or the force an agent is exerting. One aspect of Weight is the effort needed to move, which can be captured by the **acceleration** of the agent – high acceleration implies more force. In acting, Weight is also often conveyed through **posture** – a low, bent posture indicates more weight compared to an upright, extended posture. For the dancing task, we use both approaches. For calculating acceleration of an axis, the outputs are velocity (v) and acceleration (a), and the inputs are the time (t), which is calculated as the Time Effort, and angle/distance (r) to move, which is calculated as the Flow Effort (see below). Note that the axes come to a stop after each move, so the initial velocities are always zero. For the *light* attribute, we use a triangular trajectory (minimal acceleration and deceleration): $v=2r/t$ and $a=2v/t=4r/t^2$; for the *heavy* attribute, we use a trapezoidal trajectory: a=max acceleration of the axis and $v = \left(at - \sqrt{(at)^2 - 4ar}\right)/2$.

For posture, we set the base angle used by the Space Effort to be low for *heavy* and high for *light*; thus, the robots appear squashed in the *heavy* attribute and extended in the *light* attribute. In addition, in the *light* attribute, the base angle used by the Space Effort for the pitch axis is 10° above what would be directly looking at the person's head and for the *heavy* attribute it is 15° below that angle. This makes the robot look more bent over in the *heavy* attribute and more upright in the *light* attribute.

The *Flow* Effort conveys how consistent motions are; motions with low variance are considered more consistent than high-variance, exaggerated motions. Each actuator has a mean **range of motion** μ and a variance v. The calculated range of motion for the actuator is simply: μ +/- $rand(v)$, where *rand* chooses uniformly from the argument value. For the *bound* attribute, μ is used as given; for *free*, 1.5 times μ is used. For example, for the tilt axis, μ=20° and v=5°; thus, the *bound* range of motion is chosen from [15°..25°] while the *free* range of motion is chosen from [25°..35°]. For each axis, values were chosen to make the two attributes appear distinctive, while being careful not to exceed the range limits of the axes.

This approach to implementing and combining Laban Efforts has been used for different robot tasks and different morphologies [9, 11]. The implementation described here has been validated for the dancing task with both a Keepon and a Nao robot. Specifically, it has been shown through an on-line study that people can reliably distinguish the various Laban Effort attributes, even with different robot morphologies [9]. Thus, even though some parameter values were tweaked for this study from that in [9], due to issues with limits on the robots' ranges of motion, we are assuming that participants would similarly be able to distinguish the Efforts for a group of dancing Keepon robots.

IV. CHARACTERIZING EXPRESSIVE MOTION

We use the skeleton data provided by a Kinect sensor to determine the Laban Efforts of a participant. The skeleton data consists of the 3D positions of a variety of body parts, including the head, torso, shoulders, and hands, which we use for characterizing the Efforts. We have tried to be consistent with how we parameterize the Efforts for generation and how we analyze the body for characterization, subject to the differences in morphology between the robots and people and the limitations of the sensor data (see Table 1 for comparisons).

A few general comments: First, the Kinect data are noisy and so all calculations are done using a sliding window of size 10 (since the Kinect data are generated at 20 Hz, that represents a half second of data). Second, a dead band is specified for each Effort to prevent jittering between the attributes.

For the *Time* Effort, we cannot assume that the children will always be moving to the beat, so rather than looking at time directly, we are looking for the associated Time characteristic of **velocity**. Velocities are determined by the difference between successive positions of the head and hand locations. The Time Effort is determined to be *abrupt* if either the head velocity or the maximum of the two hand velocities is above a threshold; it is *sustained* if both are below a threshold (where the two thresholds differ by the dead band values).

For the *Space* Effort, we wanted to differentiate the children focused on the robots (*direct*) and looking around (*indirect*). Since the skeleton data is not able to detect head orientation reliably, we characterized the Space Effort based on body **orientation**. Specifically, we calculate the angle the shoulders make with respect to the Kinect sensor and consider the attribute *indirect* if the angle is greater than 30° or the shoulder rotational velocity (change in angle over time) is greater than 10° per second (indicating a rapid change in orientation). The attribute changes to direct if the angle is less than 20° and the velocity is less than 5° per second. We use rotational velocity as a secondary indicator because computing body orientation from the shoulder positions as given by the Kinect data is fairly noisy.

For the *Weight* Effort, we wanted to use both **posture** and **acceleration**, as is done with generating the Weight attributes. Since it is difficult, using just the skeleton data, to determine if a body is compressed or bent, we decided to use a simpler method – the **height of the hands** relative to the head. The attribute is *light* if the hands are at or above the level of the bottom of the head and *heavy* if the hands are below the shoulders. We also use the acceleration of the hands to characterize the Weight Effort, but the double differencing needed to compute acceleration from positional data tends to make it too noisy to be very useful.

For the *Flow* Effort, we wanted to capture the extent of the children's movements. While the generation of Flow motions focus on the range of movement, this was very difficult to calibrate, since we did not have a good baseline for the children's motions. Instead, we decided to use the **maximum extent** of the skeleton and the **ratio** between the maximum width and height of the skeleton. Specifically, we calculated the extent of the skeleton for all the available body parts, and computed the body extent as the difference between the maximum and minimum X values, the body height as the difference between the maximum and minimum Y values, and the body ratio as the extent over the height. As with the Efforts above, the attribute was considered *free* if either the extent or ratio were greater than some thresholds and *bound* if both were below some thresholds (which, again, are different from the *free* thresholds by the dead band values).

While the features used to characterize the Efforts are reasonably principled, given our overall approach to representing Laban Efforts, the dance task, and the limitations of the Kinect sensor, we acknowledge that the choice of parameter values is somewhat arbitrary. We tried to calibrate the parameter values through extensive testing by the researchers, but were not entirely successful, as is apparent by the fact that, in the actual study, the Flow Effort did not show much change. We attribute this mostly to poor calibration, since the researchers could observe variation in the children's extent. For future work, we would like to investigate techniques to learn Laban characterization, as is done in [27], and to incorporate probabilistic techniques, as in [6, 22], to deal with noisy data better.

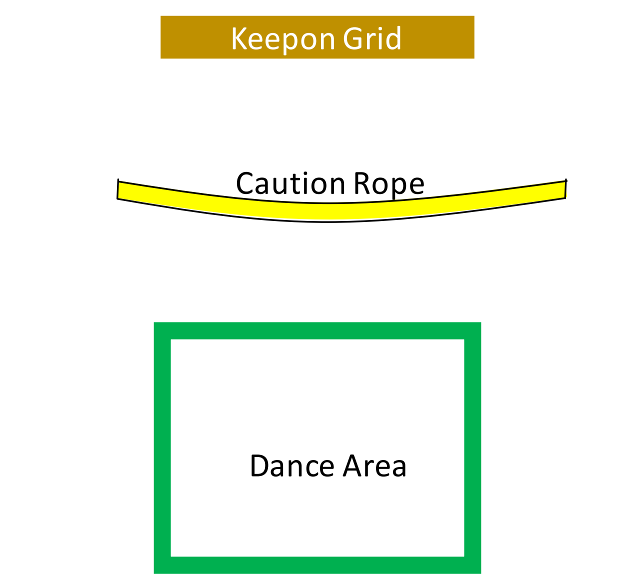

Figure 4. Study set up (top view)

V. METHOD

Eight Keepon robots [17] were arranged in a vertical 3x3 wooden grid, approximately 4' x 4' (width and height), with a Kinect sensor in the middle of the grid (Figure 1). The Keepons were controlled through software written using Max, running on a Mac laptop. The Laban characterization software was run under Max on a PC, connecting to the Kinect via the DPKinect package and connecting to the Mac using the TCP communication protocol supported by Max. Head pose data is received at 10Hz and Laban Effort data at 2Hz.

The grid was set up so that the top of the second row of Keepons was at the height of an average 7-year old, so that most of the children would not have to look up, or down, too much to see all the robots at once. The Kinect was set up to detect and track people in a 4' x 3' "dance area", whose front edge was roughly 3.5 feet in front of the Keepon grid (Figure 4). The dance area was marked on the floor with green tape, and a yellow rope was placed between the grid and the front of the dance area to discourage children from approaching too close to the robots.

The study was run over three weekends at Disney Research Pittsburgh. Participants were recruited by Disney for their "Summer Games" through announcements at Carnegie Mellon and the local community. This study was an optional exercise (with separate IRB approval), held after the participants had gone through the Disney protocols. 45 children (20 girls, 29 boys) between 5-9 years old (M=6.8 years, SD=1.8) participated in the study. Most of the younger children were accompanied by a parent and/or sibling, while most of the older children (7 and up) participated by themselves. Three additional children were recruited but did not participate because either the robots frightened them or they were unwilling to leave their parents.

The children were told that the robots would start dancing whenever the child entered the marked dance area and stop when they left. They were told that they could "watch the robots, dance with them, whatever you want" and could leave the dance area whenever they were done. The children were also told that they could go back and interact some more, and several did so.

When a child was first detected, the robot closest to the child's head (as calculated using the skeleton from the Kinect) would quickly turn to face the child and then bounce three times as a greeting. The other seven robots would then do the same thing and then the music would start and the robots would begin dancing. While the robots all danced with the same Laban Efforts, they did not necessarily move in exactly the same ways. This is because a) the generation of the Laban Efforts (Section III) involves some random choice of parameter values; and b) some of the robots start swaying to the left and some to the right. But, all the robots followed the exact same beat.

Anytime the child stayed in the low-energy Laban state (*sustained, direct, bound, heavy*) for more than 20 seconds, one of the robots would "go rogue," dancing in the high-energy state (*abrupt, indirect, free, light*); after 5 seconds the other robots would stop, turn to "stare" at the rogue robot, which would then stop and drop its head, as if in shame, and then all the robots would continue dancing. This was implemented as an attempt to engage children who otherwise seemed not to be participating in dance (as evidenced by their low-energy state).

Time-stamped data were logged on both laptops. On the Mac, logs were kept of when the child entered and exited the dance area, changes in the Laban Efforts of the participants, and every behavior change of the robots. On the PC, logs were kept of the skeleton data, as well as the computed Laban Efforts.

The study had three conditions: 1) the test condition where the Keepons mimicked the Laban Efforts of the child; 2) a condition where the robots always danced in the low-energy condition, regardless of what the child did; and 3) a condition where the robots always danced in the high-energy condition. A fourth condition, where the Keepons used the opposite Laban Efforts of the child, was abandoned after 4 trials due to technical difficulties, and is not included in the study. Two different Disney songs were used: 1) *Shake It Up* (128 beats per second) and 2) *Twist My Hips* (120 beats per second). Each song lasted approximately 2:55 and then repeated. The conditions and which song was played were randomized. In all, there were 16 participants in condition 1, 16 in condition 2, and 12 in condition 3. One original participant in condition 1 was eliminated as an outlier (she interacted for over 15 minutes, which is much greater than the 3rd quartile plus 1.5 times the inter-quartile range).

VI. RESULTS AND DISCUSSION

The main data analyzed were the total time interaction (a measure of engagement), the number of Laban Effort changes per minute (a measure of diversity) and the percentage of time spent in each Laban condition (a measure of attitude). In addition, we looked at the number of times children returned after leaving the dance area (a weak measure of engagement) and the amount of time a robot went "rogue" (a measure of participants' "energy level").

The following three tables present the basic results. The times are all given in minutes. The table below shows statistics for how long the children interacted with the robots; the *full* column indicates the percentage of participants who stayed through at least one full playing of the song.

Total Time of Interaction					
Condition	***#***	***Mean***	***Std***	***Median***	***Full***
1. Mimicry	16	2:45	1:18	2:36	44%
2. Low Energy	16	2:05	1:30	1:54	25%
3. High Energy	12	2:15	1:09	2:18	25%

The table below shows statistics for how often the system determined that the child's Laban Efforts changed per minute.

Laban Effort changes per minute			
Condition	***#***	***Mean***	***Std***
1. Mimicry	16	28.56	13.92
2. Low Energy	16	15.23	9.47
3. High Energy	12	17.57	7.31

The table below show the average percentage of time /standard deviation that it was determined that the children were in each of the high-energy Laban Effort states.

Percentage of time in High-Energy Laban Effort States					
Condition	***#***	***Abrupt***	***Indirect***	***Free***	***Light***
1. Mimicry	16	33%/27%	43%/29%	2%/5%	45%/32%
2. Low Energy	16	23%/27%	31%/28%	5%/16%	39%/39%
3. High Energy	12	16%/13%	29%/20%	2%/4%	26%/20%

5 children overall returned to the dance area after leaving: 3 were in condition 1 (one child returned 6 times, another twice), and 1 was in each of the other two conditions (returning just once, each). There is not enough data to determine if this is significant, but it is suggestive evidence of more engagement in the mimicry condition.

In addition, the robots went "rogue" on average 26 seconds (SD=21 seconds) in condition 1 and 48 seconds (SD=37 seconds) in condition 2. (The "rogue" behavior is disabled in condition 3, since the robots are always in the high-energy state). The robots went "rogue" at least once for every participant in condition 2; for 4 participants in condition 1 the robots never ended up going "rogue." This is suggestive evidence that children in condition 2 were in the low-energy state for longer periods of time than those in the test condition. We were hoping to find some correlation between having the robots go "rogue" and subsequent expressive motion of the children, but nothing was apparent.

Changes per minute are statistically significant ($F=10.16$, $p<0.001$), with nearly twice the rate of change in the test condition than the other two. This supports hypothesis 2, that children will exhibit more diversity in motions when being mimicked.

While no other result in the tables above show significance, the mean values are suggestive. In particular, the mean times for the mimicry condition are 32% and 22% higher than for the two control conditions, and the median times are 37% and 13% higher, respectively. In addition, the percentage of children who stay for at least one repetition of the song is 75% higher in the test condition. This is weak evidence for hypothesis 1, that the children in the mimicry condition interact longer (and even weaker evidence that the children in the high-energy condition interact longer than the children in the low-energy condition).

Similarly, the mean percentages of time in the various attributes suggest a tendency towards high-energy attributes in the mimicry condition. Children in the mimicry condition spent 45% and 100% more time in the *abrupt* attribute than in the two control conditions ($p=0.19$); 38% and 49% more time in the *indirect* attribute ($p=0.26$); and 15% and 70% more time in the *light* attribute ($p=0.27$). There is no real difference in the Flow Effort, which is uniformly low and shows little variation. We hypothesize that this is because the characterization of the Flow Effort was not well calibrated for children (the exception being one participant in condition 2 who was extremely active during the whole time; removing that outlier brings the condition 2 Efforts more in line with those in condition 3 for Time, Space and Flow). This is fairly weak evidence to support hypothesis 3, that children will exhibit more high-energy movement when the robots mimic their expressive motions.

Somewhat surprisingly, there is little evidence that children behave differently in the two control conditions. We included those conditions to see whether having the robot dance in a high-energy condition would make the children more likely to do the same. There is no evidence for that, at all. There is very weak evidence that the children interact longer when the robot is in the high-energy condition: the median interaction time for those children is 21% longer than in the low-energy condition, but the difference in the mean is only 8%.

There are also several significant results, and some trends, unrelated to our hypotheses. The song played is a main effect on the number of Laban Effort changes per minute: *Shake it Up* had nearly twice the rate of changes as *Twist my Hips* ($F=14.95$, $p<0.001$), and there was an interaction effect between the condition and song on the changes per minute ($F=4.59$, $p=0.02$). In addition, there were effects of the song on Laban Efforts: participants hearing *Shake It Up* spent 60% more time in the *indirect* attitude ($F=4.78$, $p=0.03$) and 58% more time in the *light* attitude ($F=3.55$, $p=0.07$). In addition, there were interaction effects between condition and song on both the Space Effort ($F=2.43$, $p=0.10$) and Weight Effort ($F=2.92$, $p=0.07$). Time Effort and time of interaction were similar, however.

While these results do not address our research question regarding mimicry, it does bolster the hypothesis that Laban Efforts can be used to detect children's attitudes, assuming that more activity and higher energy correlate with more engagement with the song being played. This may seem obvious, since music often evokes emotion and emotion can be tied to expressive motion, but it is still gratifying to see that we can detect significant differences in response to different songs.

Another significant result is a main effort of gender on time of interaction (F=4.87, p=0.03). Not surprisingly, girls interacted significantly longer on average (girls=2:55; boys=2:01), although all the other measurements were the same, except for a trend in the Weight Effort, where girls spent 58% more time in the *light* attribute than boys (F=2.43, p=0.13).

Somewhat surprisingly, no age-related effects were discerned. Regression indicated absolutely no difference in time spent dancing with respect to age. While there was a slight increase in Laban Effort changes per minute with age, and very slight decreases with age in percentage of time being in each of the high-energy conditions, the results were not at all close to being significant for any of these measures.

Subjectively, most of the children seemed engaged with the robots. The girls, especially, giggled when the robots started dancing, and especially when the one robot went "rogue." Many commented on how "cute" or "cool" the robots looked, and several mentioned that they looked like chicks or ducks. Some of the children stated that they wanted to take the robots home with them.

Only a few of the children danced enthusiastically, many of them just swayed, and some stood stock still. Several them commented that they did not like to dance. Most of the children were content to watch the robots, albeit rather intently. The variance in attitude was striking – some could not take their eyes off the robots, while almost an equal number were amused for about half a minute, and then wanted to go home. It should be stated that this study was done after the children had spent about 45 minutes with the Disney study, and the younger children, in particular, looked tired; a few sat or lay down in the dance area while watching the robots.

Several confounding factors may have contributed to the results of the study. For one, it is very possible that the children were inhibited about dancing in front of the researcher. Although the researcher tried to watch the computer monitor, not facing the children, his mere presence may have intimidated the children. On the other hand, the fact that some of the younger children had parents and/or siblings present may have made them less inhibited than those who were alone. Occasionally a parent would urge their child to dance, but most of the children did not do so.

VII. Conclusion and Future Work

This paper has presented a detailed account of how Laban Efforts are generated and characterized for the task of people dancing with robots. The *Computational Laban Efforts* generation framework [8, 11] is fairly general, and has been validated previously [9]. The characterization approach is more task-specific, but has the advantage that it is compatible with the generation approach. We believe that this is the first study to use the Laban Efforts for both generation and characterization of expressive motion in an interactive fashion, having the robots responding to the Efforts of the participants. Future work will be to further develop and synergize these two important aspects of expressive motion. In particular, we are interested in approaches to learning to characterize the Laban Efforts.

The research question underlying this study was whether mimicry of expressive motion affects children's behaviors while interacting with dancing robots. Three hypotheses were tested, relating to length of interaction, frequency of Laban Effort changes, and overall expression of Laban Effort attributes by the children. The fact that H2 is strongly supported (that is, children were more diverse in their expressive motions when they were mimicked) may say something about engagement and rapport due to mimicry, but it may also be due to curiosity by the children to investigate how the robot reacts to them. Had the results for H1 and H3 been stronger, the case for increased engagement and rapport due to mimicry would have been stronger. We believe that the suggestive evidence for H1 and H2 could indicate that more participants might produce significance – the variability amongst the children made it difficult to discern significance, if it in fact is there. We may also want to use surveys to collect more direct, albeit subjective, data about how the children feel about the robots.

One reviewer suggested that because the characterizations of Laban Efforts are noisy, it is possible that the child starts mimicking the robots, leading to a bilateral feedback loop. While the data we collected are insufficient to determine how much of the children's changes in Laban Efforts are due to this effect, it is an interesting issue that should be explored in future studies. It would also be interesting to determine how robot morphology affects the children's behavior. While our previous work indicated that people were relatively consistent in interpreting Laban Efforts with different morphologies and different tasks [9], it is very possible that robots that are more anthropomorphic will have different effects, especially as children may be more inclined to expect imitation of gestures for robots with arms and legs.

Finally, we note that we found significant differences in behavior depending on which song was being played and the gender of the participants. In particular, the indication that our approach can differentiate people's attitude towards songs, which typically evoke emotional reactions, suggests that expressive motion characterization may help robots of the future determine how best to respond appropriately to their environment, by watching and mimicking those around them (as we, ourselves, often do). Additional studies are needed to determine support for this idea. That being said, we believe that we have shown suggestive, at least, evidence for the fact that children are affected by robots mimicking them, and that mimicry of expressive motion can be a useful tool in human-robot interaction.

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