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Layering Laban Effort Features on Robot Task Motions

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ABSTRACT
Motion is an essential area of social communication that has the potential to enable robots and people to collaborate naturally, develop rapport, and seamlessly share environments. The Laban Effort System is a well-known methodology from dance and acting training that has been in active use teaching performers to overlay sequences of motion with expressivity for over fifty years. We present our methodology to layer expression on robot base motions, using the same set of joints for both procedural task completion and expressive communications, followed by early results on the legibility of our Effort implementations and how their settings affect robot projections of state.

Categories and Subject Descriptors
I.2.9 [**Artificial Intelligence**]: Robotics; J.4 [**Social and Behavioral Sciences**]: Psychology, Sociology; J.5 [**Arts and Humanities**]: Performing arts

Author Keywords
Design; Experimentation; Human factors

1. INTRODUCTION
An actor can perform a functional action, such as picking up a glass of water, or walking into a room, in different ways to express different internal states and attitudes. The objective of this paper is to provide something similar for robots – to provide a vocabulary of expressive motion that enables one to layer expressivity onto base motion. The vocabulary we propose to use is the Laban Efforts [1]. These Efforts describe how picking up that glass of water can include dynamic characteristics defining the *how* of that reach, such as timing, weight and attention to goal.

In the following sections, we provide a background describing the Laban Effort System, followed by a presentation of our model to layer Laban Effort features onto pre-existing robot task motions. We finish with a description and evaluation of how we applied this method to the head motions of a Nao robot.

2. BACKGROUND: LABAN EFFORTS
Actors typically spend years training to use their bodies to express emotions, relationships, and other aspects of their characters' internal state. Theoretical approaches to actor training are either descriptive (our focus) or psychological. Our objective is to operationalize the Laban Effort System [1], which describes dynamic characteristics that can be overlaid onto pre-existing motion paths and/or behaviors. In acting, Laban Efforts are used for both actor training and as a common language for describing motion.

The Laban Effort System is part of Laban Movement Analysis (LMA), a system for documenting human motion, first developed to record dance choreography, much like a musical score preserves sound [1]. LMA has since been used to annotate human movements in dance, drama, nonverbal research, psychology, anthropology, ergonomics, physical therapy, and many other movement-related fields [2].

Table 1. The Laban Effort System

Space: attitude to goal	*Direct*	*Indirect*
Time: attitude to time	*Sudden*	*Sustained*
Weight: apparent force	*Strong*	*Delicate*
Flow: sense of constraint	*Bound*	*Free*

The Efforts (see Table 1) read as if someone had programming in mind, conveniently specifying a library of combinable motion factors that give insight into an agent's motion. These factors include utilization of Space (direct/indirect), Time (sudden/sustained), Weight (strong/delicate), and Flow (bound/free). The polarity of each vector indicates the agent's attitude toward that category. For example, an agent's relaxed (sustained) attitude toward Time might have gradual velocity transitions. Instead of prescribing the precise meaning of the Effort combinations, the Laban Efforts describe the state space of possible expressions, given a base motion.

3. APPROACH: LAYERING LABAN EFFORT FEATURES ON ROBOT TASK
Almost all of the previous work in generating robot motion with Laban features [3,4,5,6] analyzed motions whose only purpose was expressive, exploring either affective state projections or Laban feature implementations alone. In our work, we overlay functional motions with expression (Fig. 1).

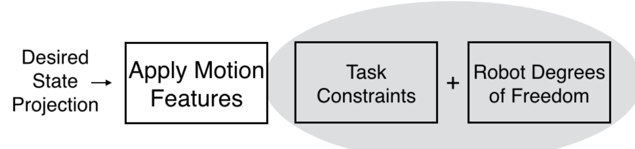

Figure 1. Approach: Layer Effort Features by DOF, subject to Robot Task constraints.

In order to do this, we specify Laban Effort features by degree of freedom. For now, we have implemented this approach on a Nao robot head (pitch and yaw) during a *look-for-someone* behavior, building on [7]. We represent Space via variance in yaw-orientation toward the detected person; Time via initial jerk in all DOFs; Weight via pitch tilt angle and acceleration in all DOFs; and Flow via yaw range of motion.

In the process, we learned that it was necessary to establish an ordering of the features, which we describe in Fig. 2. Starting with the task behavior (react to detected person), we first apply features influencing the path (Flow and Space Efforts), and then calculate the timing features along that path (Time and Weight). While a similar composition approach has been used in animation [2], we are the first to apply this ordering to robotics.

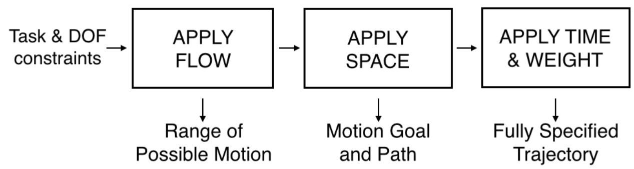

Figure 2. Laban Effort Composition: Path then Timing.

4. EVALUATION

We conducted an online study with non-experts to gain initial data about our Effort feature implementation legibility and state communications. To do so we rendered three videos representing each combination of Space, Time and Weight effort (for simplicity, we compressed Space and Flow features into a single category, *indirect* motions always *free* and *direct* motions *bound*), resulting in 24 total videos.

We display screenshots from two of these videos in Fig. 3. Note that the robot generates motion stochastically. From the images, it is easiest to distinguish the *indirect-free* motions present in the top row from the *direct-bound* motions below. The jerk and acceleration features are more visible in the motion itself.

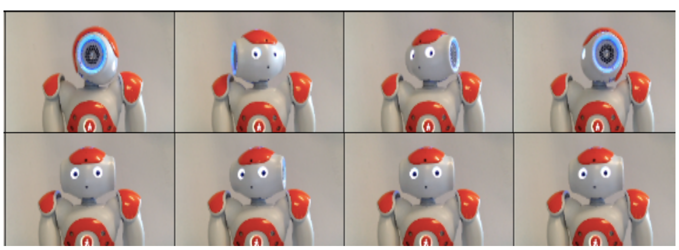

Figure 3. Screenshots from two videotaped motion sequences. The top row displays a sample with *indirect* Space, *sudden* Time, *strong* Weight and *free* Flow. The bottom displays *direct* Space, *sudden* Time, *delicate* Weight and *bound* Flow.

For each video we collected 2 semantic differential scale labels across five scales per implemented effort category. In other words, we collected 10 labels about the Time Effort, 10 about the Weight Effort and 10 about the Space Effort, resulting in 30 labels per video and 720 labels overall. The scales explored various synonyms of the Effort poles. We asked participants to watch a 20-second video, and then select the best label from a five-value scale. For example, one scale exploring the Time Effort (*sudden/ sustained)* was:

1.*Abrupt,* ***2.****Somewhat Abrupt,* ***3.****Neither* ***4.****Somewhat Leisurely* ***5.****Leisurely*

In future work, we will extend our semantic scale evaluations by comparing their results against expert labels of the same motion samples, but for now we present the results of the scales alone. Mechanical Turk workers could accurately predict the presence of the true Space Effort value for 2/5 scales, the true Time Effort setting for 3/5 scales, and the true Weight effort for 1/5 scales. We assess significance via ANOVA analysis and present the successful scales in Table 2. While the Space and Time Effort seem to be mostly legible, the Weight Effort was least detectable to laypeople.

Table 2. Significant Effort Scales (trend †, significant *)

SPACE SCALE	TIME SCALE	WEIGHT SCALE
Directed/Indirect*	Abrupt/Leisurely*	Combative/Gentle †
Obsessed/Avoiding*	Decisive/Lingering†	
	Urgent/Relaxed †	

After collecting results about what Effort implementations were legible to people, we conducted a second round of data collection to explore people's interpretations of what these motion features communicate. We asked participants to rate videos along three semantic differential scales exploring Affect (*happy/sad)*, Mental State (*confident/shy)*, and Task State (*rushed/lackadaisical)*. For example:

1*-Very Happy,* ***2****-Happy,* ***3****-Somewhat Happy* ***4****-Neither* ***5****-Somewhat Sad,* ***6****-Sad,* ***7****-Very Sad*

The resulting ratings give us an understanding of how the Effort Settings might affect the Nao robot's projection of internal state during that task. We present significant Efforts and mean ratings by pole in Fig. 4. Sustained motions rated as *somewhat sad*, *shy* and/or *lackadaisical*. *Direct* motions were likely to be rated *rushed.* Weight Effort values did not affect state predictions.

	Happy / Sad		**Confident / Shy**		**Rushed / Lackad**	
	mean (sd)	prob >F	mean (sd)	prob >F	mean (sd)	prob >F
sudden	**4.1 (1.1)**	**0.0397***	**3.9 (1.8)**	**0.0024***	**3.7 (1.5)**	**0.0003***
sustained	**4.8 (1.3)**		**5.5 (1.7)**		**5.4 (1.5)**	
strong	4.3 (1.2)	0.5536	4.6 (2.0)	0.8239	4.3 (1.8)	0.2352
light	4.5 (1.3)		4.7 (1.9)		4.8 (1.5)	
direct	4.2 (1.0)	0.1892	4.7 (0.4)	0.9409	**5.3 (1.4)**	**0.0027***
indirect	4.7 (1.3)		4.7 (2.0)		**3.8 (1.7)**	

Figure 4. Means and standard deviations of 7-point scale ratings by Effort pole, and significance by Effort category.

We have found that our Time and Space/Flow Effort features are 1) legible to untrained viewers, and 2) impactful in predicting people's attributions of the robot's state. In future work, we want to re-examine our Weight Effort features. To better quantify how functional and expressive motions interact, we would like to extend this work to a variety of robot tasks. We hypothesize that robot task will sometimes impact feature legibility and always impact the mappings between Efforts and state communications. Finally, we plan to extend our feature specifications to tilt (using the Keepon robot) and translation (using the CoBot).

5. REFERENCES

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