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# Final Project: Laban Movement Analysis and Affect

***Note: We had to re-knit the PDF after writing this paper; certain values changed due to random sampling.***

**With the availability of new hardware to incorporate overlooked modalities for interactions with computers, the fields of User Experience design and Human-Computer Interaction are witnessing a resurgence of interest in gestural interfaces. Technologies like Kinect, Leap Motion, Hololens, etc. are making it possible to reliably capture movement data from users. Simultaneously, popular concern about the disembodied experience of using computers is driving the search for media—including Virtual and Augmented Reality—that incorporate more of the expressive human body. The quest to create inspiring interactions with technology requires the exploration of different modalities for communication in order to identify user intention, communicate insights and options, and elicit affect. In this project, we are interested in human movement as a medium for communication between humans and computers. We will explore a common system for classifying affect in the valence-arousal space communicated by gestures, as well as a system for classifying the quality of gestures in the Laban effort categories.**

**A better understanding of how body language is used to convey meaning in conversation between humans will aid in more natural communication between humans and technological systems in both directions. The ability to assess affect[1] from a user's body movements will enable a better gauge of the user's needs to create more responsive systems. This would be helpful in assistive technologies like smart homes. For example, if we could determine from non-invasive camera observations exactly when a patient became frustrated and needed closer attention from caregivers, a caregiver could maintain more distance from a patient enabling both parties greater freedom and independence. The ability to communicate affect, on the other hand, would be helpful in designing more natural robots and social avatars, as well as screen-based systems, in the realms of general use, assistive technology, and entertainment.**

**Most existing gestural interfaces attempt to categorize and interpret movements based on their linguistic value, relying primarily on form-based mechanical characteristics of a movement for classification. It is clear, however, that a movement which is mechanically the same, perhaps a hand waving motion at eye level, for example, can be performed with different qualities of movement to communicate different emotional intentions. Classifying these expressive qualities of movement is the goal of many researchers in gesture-based HCI, and many different approaches are taken to solve the problem. One common approach employs the Laban Movement Analysis system—as seen in figure 1—from the field of dance, which outlines 8 movement Efforts, each of which is a combination of values for how the movement occurs in time and space with a particular weight [1]. Several recent studies have unsuccessfully used the time, space, weight, and shape affinities from Laban as guides**

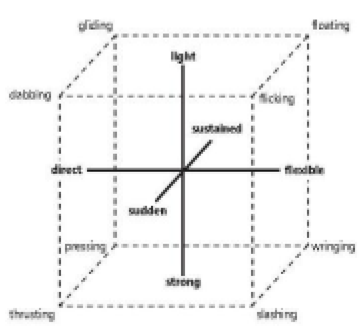


**Figure 1**: Laban effort graph with effort elements and their corresponding efforts

Laban Effort Graph
Gestures/Efforts

[1] **experience of feeling or emotion**

for the extraction of features in machine learning algorithms to classify affect [2,3,4,5]. There is not yet conclusive research assessing the relevance of the Laban effort classifications for interpreting affect. Our project was designed to explore the gap between the two classification systems of Laban and Emotion.

In approaching the problem, we referenced several papers in which Naive Bayes, decision tree, neural network, 1-Nearest-Neighbor, and linear regression models were used to classify movements in terms of affect or Laban effort [2,3,4,5]. We augmented the background information by leveraging Caitlin's domain expertise in Laban studies and movement analysis given her background in dance and physics to devise methods for extracting useful features from our movement data.

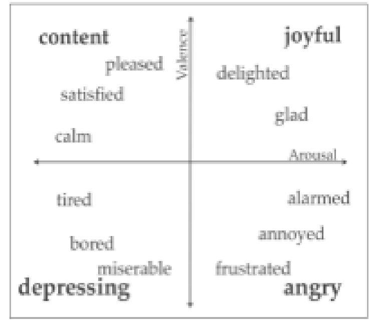


**Figure 2**: Valence-arousal space graph, where arousal reflects intensity and valence indicates emotional polarity

Our goal was to shed light on the space in which previous research has failed. Why have previous attempts that use Laban to guide the detection of affect in body movement failed? Are the features being used in the models irrelevant to Laban Effort classification? Is the data of low quality? Or is the relationship between the Effort system and expressions of affect insignificant? We collected movement data from individuals in various elicited states of affect, manually classified the Laban Efforts of algorithmically segmented movements, and devised various models to classify Effort beginning with the approach taken by Giraud's team of researchers (see Table 1 at the end of the paper for details) [2].

The raw data was obtained using the Optitrack motion capture system at NYU Magnet Mocap Labs to collect spatiotemporal data of rigid body motions. Motion samples were captured from two different test subjects of different race and gender. One test subject was a trained dancer while the other was not. motion capture data were captured from both a male and a female subject. Subjects were recorded in four different elicited states spanning the valence-arousal space: joy, anger, contentment, and sadness. Emotional states were elicited by asking participants for topics that lead them to feel each of the four emotions. Subjects were shown 2 curated videos from Youtube.com focused on the topics selected by them. Then, they were asked a series of questions while being recorded:

1. What happened in each of the videos?
2. Which video was more impactful and why?
3. What about this topic makes you feel this emotion?

| | male non-dancer | arousal | valence | emotion | emotion | video |
|---|---|---|---|---|---|---|
| emotion | content | 6 | 5 | hope | content | https://www.youtube.com/watch?v=Dha6FzM7afc |
| topic | stories | | | | | https://www.youtube.com/watch?v=hbmdOzWgyXU |
| emotion | joyful | 7 | 7.5 | excitement | nostalgia | https://www.youtube.com/watch?v=rKUD4GUWrLU |
| topic | games | | | | | https://www.youtube.com/watch?v=nyeZ8khSEC0 |
| emotion | sad | 0 | 3.5 | depressing | depressing | https://www.youtube.com/watch?v=rzmOI7fTALY |
| topic | housework | | | | | https://www.youtube.com/watch?v=GfJFBqIjPE |
| emotion | angry | 7 | 2.5 | angry | depressed | https://www.youtube.com/watch?v=Bf2JfUoXWLU |
| topic | tuition | | | | | https://www.youtube.com/watch?v=5-IuFSt5xWA |
| | | | | | | |
| | female dancer | arousal | valence | emotion | emotion | video |
| emotion | content | 3 | 8 | calm | serene | https://www.youtube.com/watch?v=9o3cvFFUNWc |
| topic | nature | | | | | https://www.youtube.com/watch?v=XhHCcH7hygo |
| emotion | joyful | 10 | 10 | happy | excited | https://www.youtube.com/watch?v=2J5GzHoKl1Q |
| topic | dogs | | | love | awesome | https://www.youtube.com/watch?v=KBluUZ4NnZg |
| emotion | depressing | 2 | 2 | sad | emotional | https://www.youtube.com/watch?v=qZMX6H6YY1M |
| topic | ungrateful children | | | shitty | | https://www.youtube.com/watch?v=958EZG0Tnlg |
| emotion | angry | 10 | 0 | frustrated | confused | https://www.youtube.com/watch?v=WhaSzIS84ks |
| topic | donald trump | | | angry | upset | https://www.youtube.com/watch?v=erKZ38lB-Gc |

**Figure 3:** Record table of test subject's emotional arousal, valence, emotion, and their curated video

Occasionally, subjects were asked more personal follow-up questions in pursuit of the desired emotional state, freeing them from self-judgments that may have prohibited expression in their movements. They were asked to report the valence and arousal of their mood during the interview to verify the elicitation of affect. Documentation of this process is available in Figure 3.

The Optitrack system features motion capture suits with reflective markers that are tracked in space and time by a system of infrared cameras positioned around the periphery of the room. The data captured is a set of numerical snapshots recorded at 240 frames per second—each frame consisting of x, y, and z cartesian coordinates (in meters) for each marker as well as quaternion rotations of rigid body parts. We chose to export only the data for x, y, and z position for each of the 49 markers at 30 frames per second to CSV files for processing. The 49 markers were positioned according to industry standards used to animate virtual characters, which we assume are a well established set of positions for capturing an optimal amount of movement detail. Below in figure 3, is a sample of the raw recorded data from the system. Each column represents a time series for a specific marker or rigid body part.

| Format Ve | 1.21 | Take Nam | AlisonAng | Capture Fr | 120 | Export Fra | 30 | Capture St | 2016-11-0 | Total Fran | 59284 | Total Expo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |
| | | Marker | Marker | Marker | Marker | Marker | Marker | Marker | Marker | Marker | Marker | Marker |
| | | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa | Alison:Wa |
| | | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C | 8392B20C |
| | | Position | Position | Position | Position | Position | Position | Position | Position | Position | Position | Position |
| Frame | Time | X | Y | Z | X | Y | Z | X | Y | Z | X | Y |
| 0 | 0 | -39.0839 | 1006.52 | 907.133 | -309.726 | 1013.57 | 858.167 | -21.662 | 990.055 | 722.799 | -268.834 | 993.936 |
| 1 | 0.03333 | -39.623 | 1006.43 | 907.492 | -310.174 | 1013.57 | 858.068 | -21.863 | 990.092 | 723.196 | -268.986 | 994.038 |
| 2 | 0.06667 | -40.038 | 1006.35 | 907.76 | -310.514 | 1013.57 | 858.086 | -22.1122 | 990.146 | 723.47 | -269.181 | 994.118 |
| 3 | 0.1 | -40.353 | 1006.32 | 907.985 | -310.8 | 1013.58 | 858.133 | -22.3292 | 990.234 | 723.675 | -269.386 | 994.226 |
| 4 | 0.13333 | -40.631 | 1006.25 | 908.199 | -311.063 | 1013.59 | 858.144 | -22.487 | 990.296 | 723.926 | -269.523 | 994.278 |
| 5 | 0.16667 | -40.8949 | 1006.18 | 908.478 | -311.278 | 1013.58 | 858.181 | -22.5765 | 990.326 | 724.207 | -269.593 | 994.319 |
| 6 | 0.2 | -41.1557 | 1006.11 | 908.791 | -311.49 | 1013.57 | 858.195 | -22.6201 | 990.385 | 724.541 | -269.596 | 994.337 |
| 7 | 0.23333 | -41.4086 | 1006.09 | 909.152 | -311.662 | 1013.59 | 858.2 | -22.6239 | 990.406 | 724.923 | -269.575 | 994.35 |
| 8 | 0.26667 | -41.6476 | 1006.04 | 909.527 | -311.827 | 1013.6 | 858.183 | -22.6031 | 990.392 | 725.301 | -269.513 | 994.335 |
| 9 | 0.3 | -41.814 | 1006.04 | 909.892 | -311.939 | 1013.64 | 858.148 | -22.5126 | 990.39 | 725.676 | -269.394 | 994.341 |
| 10 | 0.33333 | -41.9815 | 1006 | 910.246 | -312.045 | 1013.63 | 858.089 | -22.4299 | 990.362 | 726.058 | -269.286 | 994.34 |
| 11 | 0.36667 | -42.0769 | 1005.98 | 910.551 | -312.097 | 1013.65 | 858.083 | -22.3391 | 990.358 | 726.378 | -269.16 | 994.303 |
| 12 | 0.4 | -42.1147 | 1005.96 | 910.822 | -312.138 | 1013.65 | 858.113 | -22.2454 | 990.353 | 726.635 | -269.064 | 994.296 |
| 13 | 0.43333 | -42.1057 | 1005.91 | 911.036 | -312.119 | 1013.63 | 858.191 | -22.1874 | 990.376 | 726.834 | -268.977 | 994.301 |
| 14 | 0.46667 | -42.0607 | 1005.87 | 911.21 | -312.071 | 1013.63 | 858.328 | -22.1324 | 990.398 | 726.976 | -268.936 | 994.298 |
| 15 | 0.5 | -41.9481 | 1005.86 | 911.315 | -311.977 | 1013.64 | 858.511 | -22.0816 | 990.399 | 727.073 | -268.898 | 994.32 |

**Figure 4:** Small snippet of raw uncleaned data obtained from Mocap labs

The quantity, messiness (holes), and continuity of the data was not practical for the creation of a classification model for Laban Effort, so we developed a P5[2] JavaScript program to help clean, visualize, and label the data. To clean the data, we reduced the number of points considered on each body part, removed outliers and eliminated missing data. After cleaning the data, we needed to segment each time series to extract individual movements. The process of manually segmenting time proved tedious and inaccurate, so we created an algorithm to identify moving body parts and the start and end times of their movements. We separated the system into the following body parts: head, torso, chest, left arm, left hand, right arm, right hand, left leg, left foot, right leg, and right foot. Each body part was considered to be moving when ⅔ or more of its points were moving. Points were determined to be moving based on velocities above a small threshold and based on rapid accelerations and decelerations. To avoid segmenting the time for tiny jitters, we required that points be moving for about 10 frames. To account for slight variations in start and end time between different body parts, we required the number of moving body parts to stop decreasing in order to stop a movement. Segments of time were manually labeled with valence, arousal, affect, and Laban Effort. Body parts considered to be moving differently from other body parts within the segment were omitted. The final data was written to new, clean CSV files including a few new, calculated features. The final features included for each frame of each movement segment for each moving body part include: segment of time; frame time; start and end times of a movement; body part label; body part subsection (for each point); positions x, y, and z; velocity magnitude, x, y, and z; acceleration magnitude, x, y, and z; jerk magnitude; Laban Effort, emotion, valence, and arousal encodings. Laban Effort labels were separated into their appropriate values for Time, Space, and Weight, and included in the final dataset.

After most of the data preprocessing was done using JavaScript, we began to build the models. We attempted an Support Vector Machine (SVM) model, emulating the approach of Giraud, et. al. by computing statistics that include characteristics of the series over both time and space. We considered Expansiveness, Impulsiveness, Energy, Directness, and Jerkiness as outlined in the table from the Giraud paper [2]. We used these meta-features to train 3 SVMs for Time, Space, and Weight separately using the radial kernel (we tried the linear kernel with similar results). The Time SVM performed best with a precision of 0.67, a recall of 1, and an F1 measure of 0.8. This means that the SVM predicted all quick movements, which produced greater than chance accuracy because there are more quick movements. The Weight SVM was similar with a

[2] JS client-side library for creating graphic and interactive experiences

precision of 0.62, a recall of 0, and undefined F1-measure. This is because the function used to evaluate the model chose the heavy class as the positive class but predicted all light. The Space SVM, on the other hand, predicted both classes, but performed with about 0.53 precision, 0.87 accuracy, and 0.66 F1-measure, so the Space SVM essentially predicted randomly. When the predictions of all three models were combined to produce Laban Effort predictions, the composite model had an accuracy of only 0.22 as shown in Figure 5.

In an effort to improve this model, we carefully checked for outliers and problematic data. We tried included all of the data for both subjects and only the data for each subject individually. These models all performed similarly. We also tried excluding the two most popular Effort classes from the model with even worse results. In this case, the model continued to predict all the most common class, but the most common class now represented less of the considered data. We ran a Principal Component Analysis to assess the significance of each of the features, finding that all of Giraud's meta-features were significant in the first three principal components, so it did not make sense to eliminate any of the features.

Confusion Matrix and Statistics

| Prediction \ Reference | Dab | Flick | Float | Glide | Press | Punch | Slash | Wring |
|---|---|---|---|---|---|---|---|---|
| Dab | 8 | 7 | 3 | 6 | 1 | 5 | 4 | 4 |
| Flick | 2 | 2 | 0 | 0 | 1 | 0 | 2 | 0 |
| Float | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Glide | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Press | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Punch | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Slash | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Wring | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Overall Statistics

Accuracy : 0.2222

Figure 5: SVM Composite Performance

The next step was to consider other models. Originally, we had thought that the cost for K-Nearest Neighbor would be quite high. That is true for the initial data, however after the dimensionality reduction, KNN also seemed like a viable model choice. We tried a model for the emotion and effort of each individual test subject, followed by models for both subjects combined. For each KNN model, we selected the features: emotion, valence, arousal, laban, acceleration, velocity, jerk, and time. For the laban efforts, we randomly split the training set and test set eighty to twenty. Each training set contained at least eighty percent of the efforts of: slash, dab, punch, wring, press, glide, flick, and float. For the emotions, we also randomly split the training set and test set eighty to twenty of the emotions: joyful, depressed, content, angry, or none (no emotion). The results of the KNN were unimpressive as shown in Figure 6. The diagonals show the number of correct predictions, which was heavily skewed due to the amount of flicks in the training and testing sets. The predictions for emotion were slightly more successful, however, indicating the features indicative of affect may not be indicative of Laban Effort, and thus, the connection between these two classification systems may be less related than we had hoped.

knnModel_Laban

| test_target_Laban | Dab | Flick | Float | Glide | Press | Punch | Slash | Wring |
|---|---|---|---|---|---|---|---|---|
| Dab | 1 | 4 | 0 | 2 | 0 | 0 | 1 | 0 |
| Flick | 2 | 11 | 0 | 3 | 0 | 0 | 0 | 0 |
| Float | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Glide | 2 | 0 | 0 | 4 | 0 | 0 | 0 | 0 |
| Press | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| Punch | 0 | 1 | 0 | 3 | 0 | 0 | 0 | 0 |
| Slash | 2 | 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| Wring | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |

**Figure 6:** KNN results of both test subject's laban predictions, the diagonal shows the correct predictions

In order to assess the possibility that the Laban Efforts are not related to affect, we created a term document matrix for the representation of each state of affect in each Effort. In Figure 7, we can see that there is not a one-to-one relationship between affect and Effort. However, we also observe that Slash and Punch are more likely to be of a low (negative) valence, high arousal, and are probably angry. Dab and Glide

| | Slash | Dab | Wring | Press | Glide | Float | Punch | Flick |
|---|---|---|---|---|---|---|---|---|
| Angry | 13 | 9 | 3 | 0 | 0 | 0 | 8 | 47 |
| Content | 0 | 4 | 0 | 1 | 9 | 0 | 1 | 10 |
| Depressed | 1 | 6 | 5 | 5 | 9 | 3 | 1 | 6 |
| Joyful | 0 | 7 | 0 | 1 | 3 | 0 | 0 | 1 |
| None | 7 | 7 | 1 | 2 | 3 | 0 | 4 | 11 |
| Valence | 2.30 | 5.43 | 1.41 | 2.71 | 5.53 | 4.27 | 2.34 | 2.55 |
| Arousal | 5.94 | 5.42 | 5.12 | 4.80 | 3.93 | 3.36 | 4.67 | 4.97 |

Figure 7

have a higher valence and are more likely to be seen in a Joyful expression. Wring, Press, and Float are most likely to be seen in Depressed expression. A content movement is most likely to be a Glide. This suggests that there is some relationship between the Efforts and Affect, but more data and a more thorough investigation (including contextual factors) are needed to draw any definitive conclusions regarding the exact nature of the relationship..

At this point, it seemed increasingly likely that the features used in the model by Giraud and collaborators (after Camurri, et. al.) were not indicative of Laban Effort. Other possible explanations for the poor performance of our classification models were that the time segmentation was not specific enough, that there were errors in the data, or that the Laban Efforts are not an appropriate classification system for movement quality in conversational body movements. To gain greater insight, we produced plots of x position, velocity, and acceleration for a single point over the duration of four randomly selected movements from each Effort category. In the plots, units for x position are cm and the x position is vertically shifted into the range of the plot. Units for velocity are cm/s and units for acceleration are cm/s^2. A few sample plots are shown in Figure 7. The full set of plots is available in the accompanying report.

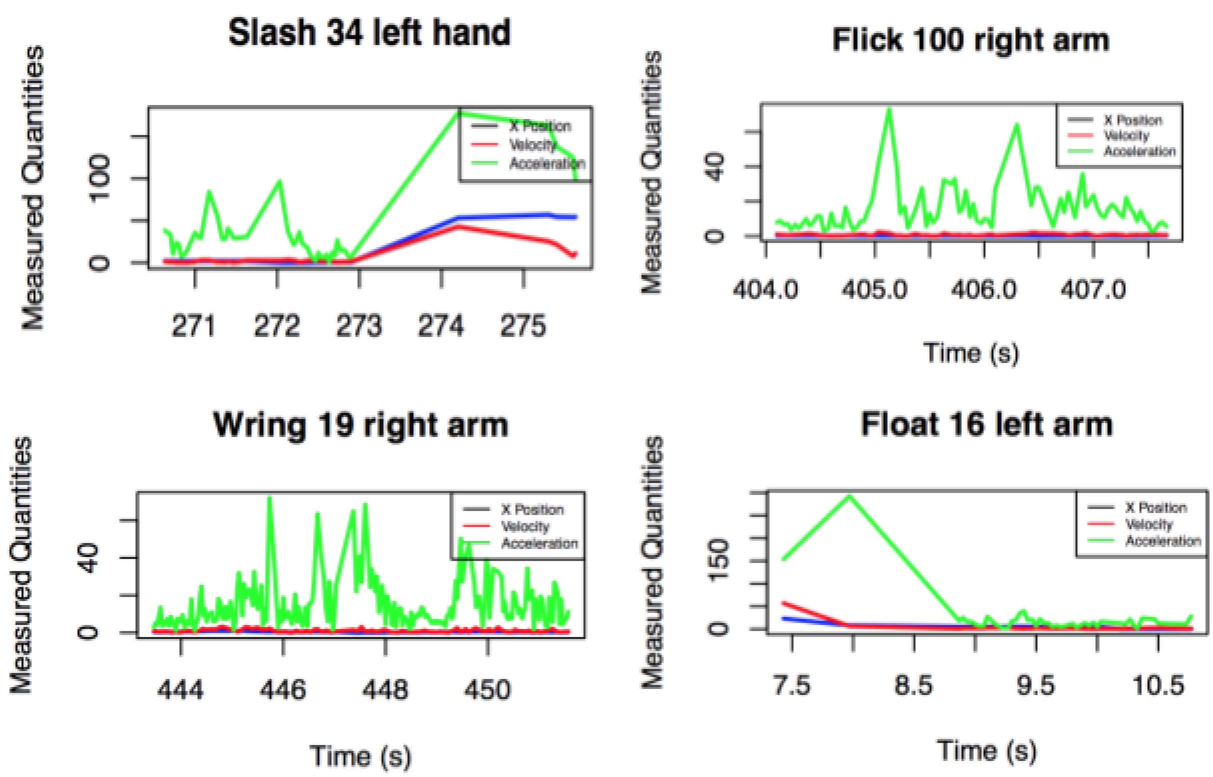


Figure 7

We notice that slow movements tend to have wider and smoother velocity bells. We observe higher and more jagged peaks in faster movements. If we look very closely at heavy movements, there appear to be more localized positional quivers. We can see these quivers and animations of Alison intentionally performing Press and Wring, and we believe they are the result of expending more energy and finding more resistance in the movements. It also appears that indirect movements have more directional changes and thus more sharp peaks and valleys in acceleration and more local quivers in velocity. We also notice that our time segmentation is probably not fine enough to for classifying movements according to specific trends in the movements over time. Future research should attempt to isolate individual movement bells rather than short

**sequences of bells. These plots guided our final approach to classifying Laban Effort using new features.**

**We observe weakness in the features used in the Giraud approach. First, the Energy feature is intended to account for differences between the heavy and light weight classes, but it is simply average kinetic energy, which completely ignores potential and chemical energy stored in the muscles and energy released as heat. These other forms of energy are much more closely related to the concept of weight as Laban intended. Second, the treatment of time in these features is flawed. Each moment in a given time segment is considered equally and interchangeably, but we know that a movement that begins slowly and accelerates will be qualitatively different from a movement that begins will rapid velocity and tapers to a halt gradually.**

**We tried a different set of features for classification. Initially, we thought about taking values for 4-6 slices of each movement segment and making each slice a feature of its own. Upon observing the plots of the data, we realized that noisiness and the arbitrary choice of these slices would result in less effective features. Instead, we tried to extract features that do not depend on the random location of peaks and troughs in noise. Guided by the plots, these features attempt to capture the maximum height of velocity acceleration, and jerk bells which could indicate Time or Directness, the timing of the peaks within the segment which could indicate directness (does the movement have a hard stop?), average value of velocity before and after the peak velocity (is the speed overall increasing/decreasing?), spikiness (how many little quivers occur?), expansiveness (how wide is the movement?), and duration.**

1. **Max. Velocity**
2. **Fraction of time segment elapse before Max Velocity**
3. **Max. Acceleration**
4. **Fraction of time segment elapse before Max Acceleration**
5. **Max. Jerk**
6. **Average value of velocity first “half” of movement / max velocity**
7. **Average value of velocity second “half” of movement / max velocity**
8. **Spikiness/Shakiness: Average of absolute values of differenced values of x, y, and z positions**
9. **Expansiveness (retained from the first approach)**
10. **Duration**

**Again, the features were calculated and the data was split into test and training sets. This time, instances of both Flick and Dab were included to reduce biases. Again, SVMs were trained for Time, Space, and Weight. The Time SVM performed fairly well with a precision of 0.71, recall of 0.97, and F1-measure of 0.82. Again, the Weight SVM predicted mostly light with a precision of 0.6, a recall of 0.23, and an F1-measure of 0.33. The Space SVM performs with precision of 0.6, recall of 0.71, and F1-measure of 0.65. This is slightly better than chance accuracy. The composite model predicts Laban Efforts with an accuracy of 0.31, which is better than chance (0.125). Complete results are shown in Figure 8.**

Confusion Matrix and Statistics

Reference

| Prediction | Dab | Flick | Float | Glide | Press | Punch | Slash | Wring |
|---|---|---|---|---|---|---|---|---|
| Dab | 2 | 4 | 1 | 4 | 3 | 1 | 1 | 0 |
| Flick | 1 | 7 | 1 | 1 | 0 | 4 | 5 | 2 |
| Float | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| Glide | 0 | 0 | 2 | 4 | 0 | 1 | 0 | 1 |
| Press | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Punch | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| Slash | 1 | 1 | 0 | 0 | 0 | 0 | 3 | 0 |
| Wring | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

Overall Statistics

Accuracy : 0.3158

Figure 8

**Based on this exploration, we cannot draw clear conclusions as to the breakdown in the efforts of previous researchers to classify affect from Laban Effort-inspired features. We can conclude that the**

**features used by Giraud, et. al. were probably not useful features for identifying Laban Efforts. We can also glean that there is some relationship between the Effort categories and states of affect, but that relationship may be too complex to use one classification system as an indicator for the other.**

**This has been an early exploration of this topic, and future studies should address many concerns:**

1. **More subjects should be recorded for analysis.**
2. **Labelling of effort and affect should be for individual body parts and very fine-grain segments.**
3. **Labelling should be verified by multiple experts.**
4. **Models for classifying Laban Effort should be trained with recordings of intentionally performed Laban Efforts and tested on conversational movements to determine the presence of Laban Efforts in conversational expression.**

**Table 1**
Descriptions and equations of time-series according to Effort and Shape qualities.

| Effort and shape qualities | Times series – descriptions | Equation |
|---|---|---|
| Time-effort | **Impulsiveness**. Time effort can be determined as the net acceleration at the body parts over time. Large values of net acceleration indicate sudden movements characterized by a high Impulsiveness | Eq. (A.1) $I_{member} = \frac{\lvert V(t_i) - V(t_{i-1}) \rvert}{t_i - t_{i-1}}$ $Vi(t)$, velocity of the segment |
| Weight-effort | **Energy**. Weight effort can be determined as energy at each instant (t) over time. $m_{member}$ is the approximation of the mass of each segment according to the Winter table (Winter, 2004). Large values of Energy indicate strong movements. | Eq. (A.2) $E_{member} = \frac{1}{2} m_{member} * Vi(t)^2$ |
| Space-effort | **Directness**. Space effort is computed as the inner product of chest and segment displacement (i.e., right hand, left hand, right foot, left foot) trajectories. Direct movements are thus usually characterized by a small number of peaks. | Eq. (A.3) $D_{member} = \vec{V}_{chest} * \vec{V}_{member} = \begin{pmatrix} V_{chest\ X} & V_{chest\ y} & V_{chest\ z} \end{pmatrix} * \begin{pmatrix} V_{member\ X} \\ V_{member\ Y} \\ V_{member\ Z} \end{pmatrix}$ |
| Flow-effort | **Jerkiness**. Flow effort is determined as the 3D curvature for each segment for each time. The curvature is a rapport between velocity and acceleration. Computation of curvature gives small values for smooth movements and high values for jerky movements. | Eq. (A.4) $J_{member} = \frac{\sqrt{(v_{xi} * a_{yi} - v_{yi} * a_{xi})^2 + (v_{zi} * a_{xi} - v_{xi} * a_{zi})^2 + (v_{yi} * a_{zi} - v_{zi} * a_{yi})^2}}{(v_{xi^2} + v_{yi^2} + v_{zi^2})^{\frac{3}{2}}}$ $v_{xi}$*and* $a_{xi}$ indicate the first and second derivatives of the segment position at frame i, respectively |
| Shape-qualities | **Expansiveness**. Shape Qualities describe the way the body is changing toward space. Expansiveness is associated to the position of each segment according to the center of mass at each time. Values of Expansiveness are close to zero for dense movements and are high for expanded movements. | Eq. (A.5) $Ex = 3/4 * \pi DI_x * DI_y * DI_z$ $DIx = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(x_{mi} - x_{ci})^2}$ $DIy = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(y_{mi} - y_{ci})^2}$ $DIz = \frac{1}{n}\sum_{m=1}^{n}\sqrt{(z_{mi} - z_{ci})^2}$ DIx, DIy, DIz are the sum of distances between the mass center coordinate $(x_{ci}, y_{ci}, z_{ci})$ and the n-th segment coordinate $(x_{mi}, y_{mi}, z_{mi})$ at frame i |

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