Desiging For Movement: Evaluating Computational Models using LMA Effort Qualities

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ABSTRACT
While accelerometers have been used in movement recognition systems, acceleration data is rarely used to assess expressive qualities of movement. We present a prototype of wearable system for the real-time detection and classification of movement quality using acceleration data. The system applies Laban Movement Analysis (LMA) to recognize Laban Effort qualities from acceleration input using a machine learning software that generates classifications in real time. Existing LMA-recognition systems rely on motion capture data and video data, and can only be deployed in controlled settings. Our single-accelerometer system is portable and can be used under a wide range of environmental conditions. We evaluate the performance of the system, present two applications using the system in the digital arts and discuss future directions.

Author Keywords
Movement recognition, Movement analysis, Laban Effort analysis, movement analysis, movement-based interaction

ACM Classification Keywords
I.5.2 Pattern Recognition: Design Methodology---Classifier design and evaluation; H.1.2 Models and Principles: User/Machine Systems---Human information processing; I.5.1 Pattern Recognition: Models

INTRODUCTION
Within human computer interaction (HCI) movement was originally understood as a functional component of interaction. This design approach reflects the task-oriented focus of early HCI research, which was preoccupied with ergonomics and efficiency as exemplified. Yet, movement is not solely functional, it is also highly expressive and experiential.

Movement analysis systems such as Laban Movement Analysis (LMA) have a rich epistemological history particularly in the domains of dance, non-verbal communication, psychoanalysis and psychology providing rigorous explanatory models for the description of movement [15], its function and its expression. LMA has been used in previous computational systems, to interpret the physical movements of robot agents as outward manifestations of internal emotional states [2], to generate physically expressive animated characters [8], support social intimacy by interpreting qualities of touch applied to networked, tactile interfaces [24], and classify activities such as walking and running [13]. Yet, within HCI, the application of LMA theories, principles and models remains marginal and most of the time incomplete or compressed.

The general goal of our research is to explore how movement expertise from LMA can lead to the design and integration of more richly articulated human movement knowledge within movement-based interaction. In particular, we are interested in the notion of "movement qualities" (MQs) that practitioners and theorists of movement define as the qualitative characteristics defining the manner in which a movement is executed. LMA formalizes MQs into the Effort category (the other categories being Body, Space, and Shape). Laban describes the movement's Effort according to four factors: Space, Time, Weight, and Flow. Each factor has two elements (Space: direct/indirect, Time: sudden/sustained, Weight: light/strong, Flow: bound/free) that can be understood as two ends of a continuum in which the movements can vary and thus reveal different qualities or "Effort qualities". Laban considers the Effort qualities as expressive attributes of movement produced by dynamics. Although MQs are a central notion that conveys movement expressiveness, they haven't been explored in designing and evaluating human-computer interactions until lately [9,16,26]. We believe that because MQs reveals movement expressiveness, their use has strong potential for movement-based interaction with applications in the arts, digital media, entertainment, education, or rehabilitation. Precisely, our work aims at designing and evaluating interactive systems where the notion of MQs is central, and that provide feedbacks that can inform users about their MQs. Our systems include MQ analysis (motion capture, feature extraction, and real-time recognition), as well as MQ synthesis and control through for example sound or visual feedback (given the extracted MQs).

In this paper, we present the design and evaluation of a prototype of MQs analysis system called EFFORTDETECT that uses motion data from a single accelerometer fed to a machine learning software to recognize in real-time and classify Laban Effort qualities. While most of the Effort recognition techniques in the literature rely on motion capture or video data, which require careful positioning of a subject and cameras, our system is based on a single-accelerometer to perform continuous MQs classifications. Acceleration data are directly linked to movement dynamics that produce MQs and thus offer a coherent alternative to positional data when feeding the recognition process of MQs. Moreover, the advantage of using accelerometers is that they are small and thus highly portable, and can be used under a wide range of environmental conditions especially for interactive installations targeting general audience or interactive performances. Moreover, we will present two artistic applications that uses EFFORTDETECT to capture the performer's MQs an integrate it as an interaction modality.

LABAN MOVEMENT ANALYSIS

In this section, we present the LMA system in order to clarify how we use it to define a framework for MQs recognition and evaluation.

Factor	Indulging Value	Fighting Value
Space	*Indirect* Flexible, meandering, wandering, multi-focus	*Direct* single focus, channeled, undeviating
Weight	*Light* buoyant, delicate, overcoming gravity	*Strong* Powerful, having an impact
Time	*Sustained* lingering, leisurely	*Sudden* hurried, urgent
Flow	*Free* uncontrolled, abandoned, unable to stop	Bound controlled, restrained, able to stop

Table 1. The Effort factors and their extreme values.

LMA looks at movement through four different categories of *Body*, *Space*, *Effort*, and *Shape* [15] that comprise a rigorous and systematic framework for understanding and categorizing movement. The Effort component describes human MQs using four factors: *Space*, *Time*, *Weight*, and *Flow*. Observable qualities of Effort mark the outer manifestation of an inner attitude. Each of the Effort factors is a continuum bounded by two extreme values (Space: direct/indirect, Time: sudden/sustained, Weight: light/strong, Flow: bound/free) in which movement can vary and thus reveal different qualities or "Effort qualities". One of the values is the result of "indulging" through the Effort, while the other extreme value is the result of "fighting" through the Effort [14]. Space is related to the subject's attention to the surrounding environment, and the directedness of their interaction with it. Time is related to the subject's sense of urgency. Weight is related to the subject's sense of presence in the world and the impact they make upon it. Flow is the feeling of "aliveness" and the attitude towards bodily control. Table 1 lists the indulging and fighting values for each Effort factor and the internal attitudes related to each.

Not all the Effort factors play a significant role at all times. One or more of the Efforts may be attenuated during a movement. Laban denotes by *Action Drive*, actions with MQs where Flow Effort is not emphasized. To delimit the *Action Drive*, he combines the extreme values of Space, Time, and Weight Effort into what he calls the eight Basic Effort Actions (BEAs). The BEAs, outlined in Table 2 are not movement *per se*. When waving one's hand goodbye, for example, the movement could have either a *punching* quality or a *floating* quality. The BEAs can thus be treated as qualitative descriptors of movement that combines three Effort factors. Because these actions are prevalent in daily activity and because they cover a large range of Efforts, qualities and dynamics, we chose to train our EFFORTDETECT computational model to recognize and classify them in real time.

Space Factor	Time Factor	Weight Factor	Basic Effort Action
Direct	Sustained	Strong	*Press*
Direct	Sustained	Light	*Glide*
Direct	Sudden	Strong	*Punch*
Direct	Sudden	Light	*Dab*
Indirect	Sustained	Strong	*Wring*
Indirect	Sustained	Light	*Float*
Indirect	Sudden	Strong	*Slash*
Indirect	Sudden	Light	*Flick*

Table 2. The BEAs of Laban Action Drive

BACKGROUND

In this section, we review computational approaches to Laban Efforts recognition as well as the literature on the use of accelerometers for movement recognition to provide the context for EFFORTDETECT's model of MQs recognition.

Computation Models of Laban Efforts

The rich framework of MQs provided by LMA contributes to its appeal in the field of Computer Science. Indeed, most models that incorporate MQ analysis and/or synthesis rely on the Effort and Shape categories of LMA [19,21,23,29,31,32]. Some of the earliest work taking MQs into account in computer animation comes from Norman Bradler's research group. They developed the EMOTE system to animate a 3D character using Laban's Effort and Shape qualities in order to produce more expressive and natural simulated movements [8]. They also developed movement segmentation techniques along the Laban Effort factors, using high-level movement descriptors inspired by the eight Effort elements [7]. LMA Shape qualities were exploited by Swaminathan et al. and used to train dynamic Bayesian networks for MQ recognition [29].

In Human-Computer Interaction, some remarkable systems have been exploring LMA. Laban Effort qualities inspired a theoretical framework for the design of "graceful" movement-based interactions proposed by Hashim et al [9]. Schiphorst uses eight BEAs defined by Laban that convey different combinations of Effort qualities, in order to enhance the aesthetic appreciation of digital art by better involving the body of the user in the experience of interacting with digital media [25]. Schiphorst et al. also use Laban Effort actions to interpreting qualities of touch applied to networked, tactile interfaces [24]. More recently, Mentis and Johanson proposed a study that aims to situate the perception of MQs, in ones own movement and in another's movements [17]. For this purpose they built a Kinect-based system for an improvisational dance performance where audience members MQs as defined by Laban Efforts, are used to influence the music.

Most of the existing approaches of Effort recognition use positional data taken either from motion capture systems or video data. These require the subject to be positioned in a constrained way in relation to a camera or to a motion capture setup. Additionally, these approaches require the movement to be a priori partitioned into discrete segments before the classification is performed. Bindiganavale delimits the segment boundaries by computing the zero-crossings of acceleration data and detecting local velocity extrema [5]. Zhao extracts a curvature feature from motion capture data and segments movement where extreme changes in the curvature are accompanied by zero-crossings in the acceleration data [32]. These approaches to motion segmentation presume that motion is a series of discrete segments and each segment embeds an independent set of Laban Effort qualities. Our approach doesn't reauire to segment the movement and maps to movement theories articulated by Laban, Bergsen, Sheets-Johnstone, and other movement philosophers who understand movement as continuous and nondiscrete [4,28].

Accelerometer-based Movement Recognition

Accelerometers built into mobile phones and gaming devices such as the Nintendo Wii Remote have popularized mobile applications that rely on movement recognition. Accelerometers have been mostly used for tasks such as navigation [1], pointing [30], gesture-based authentication [10], or text input [12]. These single-accelerometer systems usually include movement properties such as its contours [1], orientation, tilt and direction [6], but only few of them take into consideration the dynamical or temporal component of movement by including for instance variation of speed and acceleration (which are crucial to the notion of MQs) [27]. However, some accelerometer-based systems have explored aspects of MQs for example, when recognizing semaphoric signals such as shakes, whacks, or bumps [6], which all have Direct and Sudden qualities. Roudaut *et al*. incorporate aspects of MQs in their design of the TimeTilt system, which differentiates between smooth and jerky tilting of their accelerometer-equipped device [22]. Khoshhal *et. al.* report using a system of six accelerometers to extract Time Effort, but no other components of MQs [13]. Our prototype is the only portable, single-accelerometer-based system that is designed to recognize a wide range of MQs including three of Laban Effort factors. It can be ported to existing mobile devices by using the mobile device's built-in accelerometer and interfacing it with an application that can process the acceleration data.

SYSTEM DESIGN

We designed the EFFORTDETECT system based on the knowledge and embodied practice provided by the LMA system.

Wearable Accelerometer

EFFORTDETECT uses data from a single wearable accelerometer. Although acceleration can be derived from positional data, collecting acceleration data is a more natural fit to motion dynamics and thus MQs recognition than capturing positional information. More generally, LMA analyses human movement as the *process of change*, any change of Body Effort Shape or Space, rather than the positions within the trajectories traced by a movement [4].

Technically, our Wearable Acceleration Sensor Unit is composed of a wireless transmitter and a 5DOF accelerometer sensor mounted on a microcontroller and powered by a 3.7-volt battery. The sensors transmit acceleration data from the x, y, and z axes as well as pitch and roll acceleration data. The wireless transmitters send the acceleration data to the Hardware-Software Interface once every 10 milliseconds. A Wearable Acceleration Sensor Unit is sewn into a 4-inch wide elastic fabric band that is attached to the dancer's right arm, as shown in Figure 1.

EFFORTDETECT's use of wireless transmitters and acceleration sensors implies that the system can be used in low-light situations where a computer vision-based method would perform poorly. Our wearable hardware system prevents from body part occlusion witch is a concern in both computer vision-based tracking and in passive and active IR tracking. While occlusion is not a problem with magnetic motion tracking systems, the need of both IR and magnetic tracking to process the data from multiple moving bodies are cost-prohibitive compared to EFFORTDETECT [20]. Moreover, computer vision-based methods often rely on multiple viewing angles for greatest accuracy, making these methods unsuitable in situations where ideal lines-of-sight cannot be established, such as spaces that contain obstacles, *e.g.* furniture, or outdoor spaces that do not allow cameras to be placed in optimal locations. Furthermore, EFFORTDETECT's hardware subsystem allows the computers processing the motion data to be located a long distance away from the moving bodies.

Figure 1. The Wearable Acceleration Unit

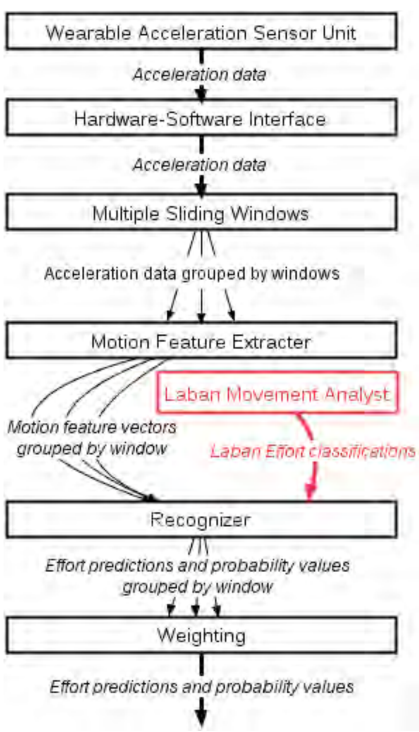

Figure 2. The EFFORTDETECT'S architecture. Components in red are active in the training phase

Multiple Sliding Time Windows

Because we consider human movement as a dynamic, continuous flux [3,18], we designed the EFFORTDETECT system using multiple sliding time windows approach rather than an a priori motion segmentation approach. EFFORTDETECT adapts a sliding window system first described by Widmer and Kubat [27] and analyzes movement data incrementally by examining it in context across three time scales. Each time scale view is a sliding time window, where the incoming data displaces the oldest data in a circular buffer. We define three windows, $w_{L,i}$, $w_{M,i}$, $w_{S,i}$ to represent a large window containing L samples, a medium window containing M samples, and a small window containing S samples, respectively, where $L > M > S$. These three sets of motion samples are passed on to the Motion Feature Extractor (see next section); at time t_{i+1}, we generate windows $w_{L,i+1}$, $w_{M,i+1}$, and $w_{S,i+1}$, which discards the earliest sample in each window and appends a new sample to each window. We note that in our implementation, we find that at a sampling rate of 100 samples per second, $L = 200$, $M = 150$, and $S = 50$ produce good results.

Motion Features

The Motion Feature Extractor examines the data in each time window and produces motion feature vectors, one per window, which summarizes the character of the motion within the time scale of each window. For every window $w_{n,i}$ of size n, we compute a *motion feature vector collection* $M_{n,i} = \{ X_{n,i}, Y_{n,i}, Z_{n,i}, P_{n,i}, R_{n,i} \}$, where $X_{n,i}, Y_{n,i}, Z_{n,i}, P_{n,i}, R_{n,i}$ are *motion feature vectors* associated with window $w_{n,1}$, composed of 9 real-numbered *motion features.* The motion features are normalized. Since every motion feature is associated with a particular degree of freedom, for a particular window, for a particular sensor, for a particular time step, we generate 9 motion features x 5 motion feature vectors x 3 motion feature vector collections x 3 sensors = 405 motion features per time step.

To describe the nine motion features we extracted, we present as an example a time window, $w_{n,i}$, of size n at time step i, and motion sample x_i along the x-axis from the window. A similar analysis can be made for motion samples in the *y, z, p*, and *r* axes.

1. We compute a current difference feature as the signed difference in value between the current motion sample value, x_i, and the one immediately preceding it, x_{i-1}.
2. The average difference is the mean of all the current differences in the window. We compute the ratio of the current and average difference features
3. We define the trajectory of x_i to be the slope of the line determined by the line passing through x_i and x_{i-1}, and the current trajectory to be a value associated with the current time step.
4. The average trajectory is defined as the average of the trajectories of all n samples within the current time window. We compute the ratio of the current trajectory on the average trajectory.

5. The number of direction changes describes the number of times where the motion switches direction along the axis. We compute the ratio of the number of direction changes per number of samples in window and per duration of the window.
6. Finally, we define a threshold value determined by recording the *x* value of the accelerometer at rest, below which we consider the sensor to be still. We compute the ratio of stillness to overall motion given by the number samples that represent the sensor at rest divided on the number of samples that represent the sensor in motion.

Recognition process

EFFORTDETECT is based on a supervised learning system built using Max/MSP and Java and using a classifier implemented in Weka[1], an open source collection of data mining and machine learning algorithm. The stream of incoming feature vectors are fed to classifier that operates in a training phase and a performance phase. During the training phase, the dancer in collaboration with Laban Certified Movement Analyst (CMA) recorded examples of the BEAs. Based on these examples, the recognition process is able, during the performance phase, to estimate in real-time the similarities between the BEAs performed by the user and those of the pre-recorded examples and decide on the BEA that is most likely to be performed by the user. Precisely, during the performance phase, the system outputs a continuous stream of classifications, which we call the BEA profile stream i.e. recognition rates or confidence values associated with each of the eight *BEAs*, rated from 0 to 1, for each of the time windows. Figure 2 shows the subsystems and the data they generate. The system examines the motion at all time scale windows and combines them to produce a single *BEA* profile stream. Depending on the target *BEA* under consideration, the system weights the output from different time scale windows. For example, quick *BEAs* such as Punch may occur within half a second or less, but they would be lost in the context of a five-second window. To detect the occurrence of these quick motions, we give heavier weight to the results of the shortest time window than of the longest time window. This approach supports continuous analysis of motion over time, and allows us to examine complex composite motion (interesting combinations and sequences of motion) over a variety of time scales.

SYSTEM EVALUATION

Experimental procedure

We conducted an evaluation session with a dancer who has studied LMA as part of her university-level dance training and a Certified Laban Movement Analyst (CMA). The evaluation session was structured into several components. We organized an *LMA knowledge exchange session* where the movement analyst worked with the dancer to ensure that the dancer was performing the *BEAs* to a degree that was legible to the analyst. We then recorded the dancer performing eight *BEAs* ten times, in random sequence, while the analyst confirmed the legibility of each performance. Finally, we did an *open-ended interview* where we encouraged the dancer and the CMA to share observations and provide feedback on EFFORTDETECT and any aspect of the evaluation session itself.

We would like to emphasize that although the evaluation uses only one dancer and one CMA, these two participants are experts, highly trained in the Laban Movement Analysis system. When movements that exhibit the eight BEAs are performed, certified analysts can unambiguously and consistently recognize their presence and with little variation in performance. In other words, the categories are consistently identified. Our expert review of the system relies on the connoisseurship that is developed and refined by movement experts, and on which previous LMA-recognition research has also relied.

Profile number	Dab conf	Flick conf	Float conf	Glide conf	Press conf	Wring conf	Slash conf	Punch conf	1st-dominant *BEA* ($e_{m,1}$)	2nd-dominant *BEA* ($e_{m,2}$)
1	0.035	**0.442**	0.025	0.	0.	0.006	0.	**0.451**	**Punch**	**Flick**
2	0.040	**0.392**	0.025	0.	0.	0.008	0.	**0.377**	**Flick**	**Punch**
…	…	…	…	…	…	…	…		**…**	**…**
99	**0.226**	0.101	0.052	0.006	0.	0.006	0.	**0.451**	**Punch**	**Dab**
100	**0.181**	0.034	0.063	0.023	0.	0.007	0.	**0.451**	**Punch**	**Dab**

Table 3. Example of *BEA* profile stream for a 1-second gesture (target *BEA* = Punch) determining the 1st- and 2nd-dominant *BEA* using profile-centered analysis

Data collected

We collected 80 profile streams that we recorded using a custom tool built in Max/MSP to assess quantitatively the performance of the EFFORTDETECT system.

[1] Weka Data Mining Software http://www.cs.waikato.ac.nz/ml/weka/

RESULTS AND DISCUSSION

Data Analysis

In this evaluation, we measure the *accuracy* of the recognition (i.e., how accurately the system chooses the dominant *BEA* in a movement from the eight possible *BEAs*) and the *confidence* of that recognition. Consider a BEA representing a Punch performed over the duration of 1 second. Since EFFORTDETECT produces a *BEA* profile every 10 ms, it generates 100 Effort profiles for the gesture over 1 second. To assess the accuracy and the confidence of the recognition for a profile stream with respect to the target effort, we compute a profile-centered analysis that determines the *nth*-dominant *BEA* (denoted $e_{m,n}$) as the effort in profile *m* that has the *nth* highest confidence (denoted $p_{m,n}$). The *nth*-dominant *BEA* for the stream (denoted E_n) is the *BEA* that appears most frequently in $\{e_{1,n}, e_{2,n}, e_{3,n}, \ldots, e_{M,n}\}$, where M is the number of profiles in the stream. The *nth*-dominant recognition confidence for the stream (denoted C_n) is the mean of all $c_{m,n}$ assigned to $e_{m,n}$ where $e_{m,n} = E_n$ for $1 \leq m \leq M$. Table 3 summarizes these measures for the profile streams of a punch; due to space constraints, we show only the first two and the last two profiles.

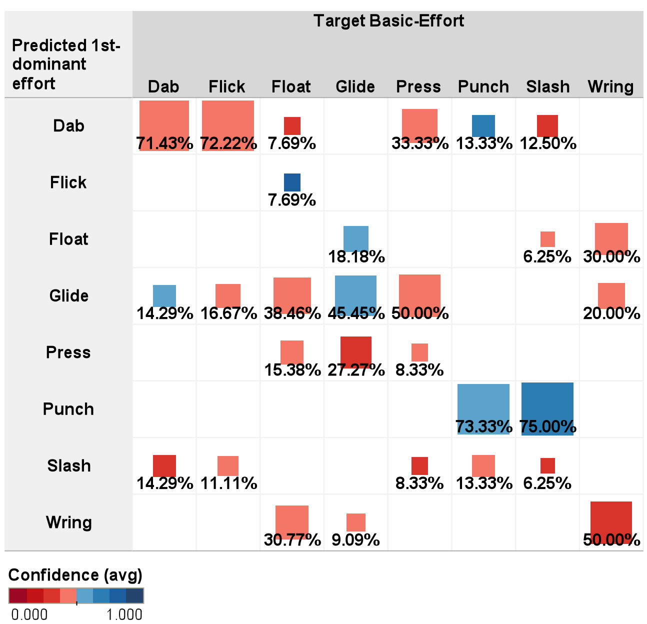

Figure 3. Modified confusion matrix using a simple, profile-centered interpretation of profile streams

Analysis of Accuracy

We compute the accuracy value of the system by analyzing whether the target BEA is recognized or not. We define $r_{m,n}$ to be the Boolean value associated with $e_{m,n}$ (the *n*th-dominant *BEA* in profile *m*), where $r_{m,n} = 1$ if $e_{m,n}$ is the target BEA and $r_{m,n} = 0$ if otherwise. We define R_n to be the accuracy value of the *n*th-dominant *BEA* in the entire profile stream, and is computed as the average of $r_{m,n}$ for $1 \leq m \leq M$. The average of the simple accuracy values, as well as the average of the 1st-dominant recognitions for all profile streams is summarized in the confusion matrix in Figure 3. Because of the different number of profiles we used for each target effort, we express the entries of the matrix in percent, computed by using the column sum as 100%. For example, 10 of the 14 gestures that were performed with the target effort of Dab were classified as a gesture with a 1st-dominant *BEA* of Dab; hence, the value in the Dab/Dab entry is 71.43%. The size of the squares is scaled to match the numerical values in the entries, while the opacity represents the average confidence associated with the recognition. The notable results shown in Figure 3 include high accuracy and confidence values for Punch and Glide recognition, a strong tendency to confidently misclassify Slash as Punch, and strong Dab and Wring recognition accuracy but with low confidence.

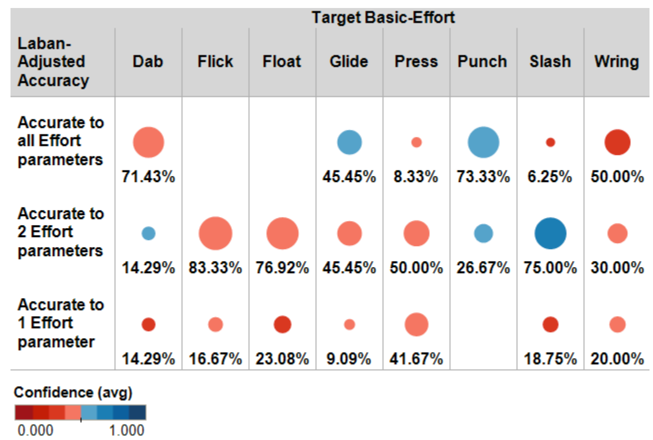

Figure 4. LMA-adjusted accuracy for 1st-dominant *BEA* recognitions

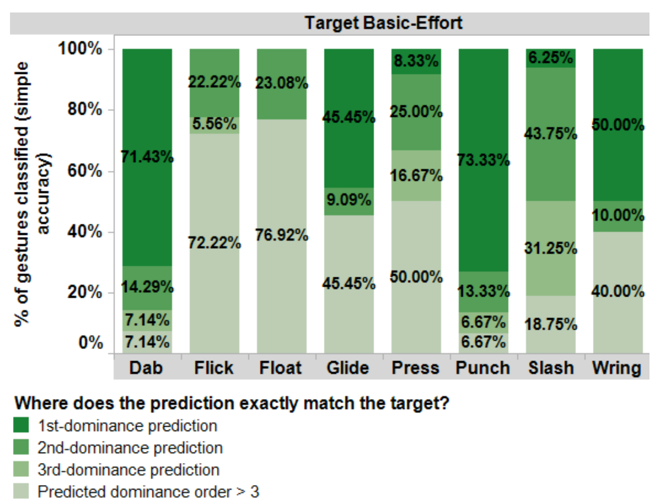

Figure 5. Simple accuracy by dominance order

LMA-adjusted Analysis of Accuracy

A simple analysis of accuracy ignores the fact that the eight *BEAs* have fundamental similarities. For instance, Dab

(*Light, Direct, Quick*) and Flick (*Light, Indirect, Quick*) differ only in their Space parameter. In contrast, Dab and Slash (*Heavy, Indirect, Quick*) differ by two Effort parameters. Figure 3 indicates that EFFORTDETECT often mistaked a Flick for Dab (72.22%). However, the results of the interviews of the CMA contrasted this, since she stated that these variations were consistent with her experience of LMA highlighting the degree of movement variability and complexity that occurs within movement streams, but that certain other kinds of classifications would not be as admissible. *For instance, it would make little sense if Dab were classified as Wring (*Heavy, Indirect, Sustained*), and even less sense if Dab were classified as Slash (*Heavy, Indirect, Quick*)*.

Following the movement analyst's observations, we propose an *LMA-adjusted analysis* of accuracy that appropriately weights the contribution of each predicted 1st-dominant *BEA* within a profile when calculating the 1st-dominant *BEA* for the profile stream. Instead of a confusion matrix, a comparison of LMA-adjusted accuracy values—averaged across profile streams and grouped by target effort—is more appropriate. Figure 4 graphs the distribution of LMA-adjusted accuracy values across the eight target *BEAs*. It expands on the report from Figure 4 in a way that is aligned with LMA-based analysis. Profile streams associated with Glide and Wring targets demonstrate complete Effort parameter accuracy more than 45% of the time (Glide: 45.45%; Wring: 50%), and accuracy to within two Effort parameters at least 30% of the time (Glide: 45.45%, Wring: 30%). Profile streams associated with Dab and Punch targets are accurate to within all Effort parameters more than 70% of time (Dab: 71.43%; Punch: 73.33%). Profile streams associated with Flick, Float, and Slash targets are accurate to within two Effort parameters at least 75% of the time. Figure 4 also reveals that no profile stream was *inaccurate* by all three Effort parameters.

Dominance Order Analysis

Figure 4 shows that 1st-dominance matching for Flick, Float, and Slash targets is inaccurate by a degree of only one Effort parameter between 75% and 83% of the time. This finding suggests another line of inquiry: at which dominance levels are these *BEAs* exactly recognized? Figure 5 visually charts the answer and reveals that profile streams for the Slash target exactly matches all Effort parameters in the predicted 2nd-dominant *BEA* 44% of the time. This shows that though the system is often (75%) confident that Punch is present in a Slash-based movement, the system's next best guess is more accurate 43.75% of the time

COMPARISON WITH EXISTING SYSTEMS

We would like to emphasize that while EFFORTDETECT does not outperform LMA-based recognition systems described in the literature, we stress the significance of the results given that the data comes from a single accelerometer attached to only one body part, unlike the systems reported by Zhao and Badler (seven body parts) [31], Rett *et al.* (two body parts) [21], and Santos *et al.* (three body parts) [23]. Indeed, Zhao and Badler [31] used magnetic trackers and video and reported a recognition rate of about 90% for Effort Weight, Time, and Flow values. Rett *et al.* [21] use Bayesian reasoning to perform continuous classification on video data to detect Effort Time and Effort Space, but not Effort Weight. They report success rates between 75% to 92% in distinguishing between the four *BEAs* with Light Weight: Flick, Dab, Glide, and Float. Santos *et al.* [23] achieved recognition rates between 58.7% and 97.1% for Effort Space, Effort Weight, and Effort Time.

To compare EFFORTDETECT's performance with other LMA systems, we compute a weighted overall detection accuracy as *(rate of perfect parameter matching + 2/3*(rate at which two out of three parameters are matched) + 1/3*(rate at which one out of three parameters are matched*) at the 1st-dominance recognition level, as summarized in Table 4.

In this paper, our main contribution is not the movement recognition system itself. We do not claim that EFFORTDETECT outperforms other LMA-based recognition systems. Rather, we believed that a significant amount of movement quality information can be recognized from a computationally efficient, real-time single accelerometer-based sensor that is readily wearable and deployable.

Basic-Effort	Weighted accuracy
Dab	80.97%
Flick	61.11%
Float	58.97%
Glide	78.78%
Press	55.55%
Punch	91.11%
Slash	62.5%
Wring	76.67%
Average	**70.71%**

Table 4. Accuracy for *1st*-dominant recognition

APPLICATIONS IN DIGITAL PERFORMANCE

EFFORTDETECT's system was successfully used in various applications in the digital performance and interactive installations.

Astral Convertible

EFFORTDETECT's system was successfully used in a live restaging of choreographer Trisha Brown's piece, *Astral Convertible* (shown in Figure 6), at the Krannert Center for the Performing Arts at the University of Illinois at Urbana Champaign. Dancers performed choreographic material that was accurately recognized by software built on the same backend as EFFORTDETECT [20], thus demonstrating EFFORTDETECT's applicability in the field.

Figure 6. Image of Trisha Brown's piece, Astral Convertible

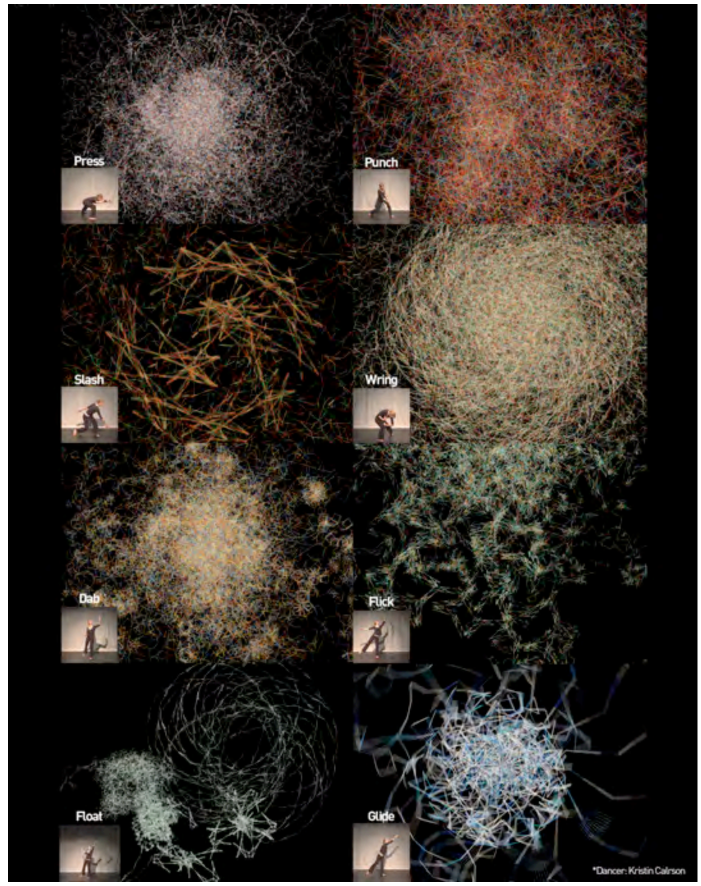

Figure 7. EMVIZ visual metaphors mapping Laban BEA to parameterized abstract visualizations

EMVIZ visualization

In the fields of human movement analysis, artistic visualization, and interactive dance performance, EffortDetect has also been used in the EMVIZ visualization system[2] (shown in Figure 7) to explore visual metaphors by mapping movement qualities, in the form of Laban BEAs to parameterized abstract visualizations. The motivation for this project comes from the interest and expertise about human movement in the field of contemporary dance performance and artistic visualization. The visualization system places attention on aesthetics, provides real-time response through models from expertise-based knowledge on properties of movement. EMVIZ uses metaphoric mappings that rely on artistic interpretation of human MQs to generate visual forms, and illustrate the creative design process for communicating expert knowledge around movement. EMVIZ was used in an interactive art installation during which the audience provided critical feedback regarding their response to the aesthetic and communicative properties of the visualizations. Audiences reported the system's ability to support their ability to become aware of engage in, differentiate and furthermore, appreciate various MQs based on the changes in their own or alternatively in a dancer's movement, with the aid of EMVIZ.

[2] EMVIZ system http://metacreation.net/index.php?s=projects#top

CONCLUSION

EFFORTDETECT is a single-accelerometer system that recognizes in real-time Laban eight Basic Effort Actions and can be used under a wide range of environmental conditions. In designing and evaluating the EFFORTDETECT model, we applied quantitative approaches to assess the accuracy of our computational system to match our conceptual and epistemological goals. Its form factor makes it an ideal candidate for use in mobile and handheld devices. The analysis of the data indicates that the model recognizes MQs to various degrees of accuracy and confidence, and that in most cases both the systems level of accuracy and performance could be described and rationalized by the LMA analyst.

The main contribution of this paper is our approach to using expertise in planning and carrying out an evaluation for movement recognition systems rather than proposing a new movement recognition system. This, we argue, is of significant interest to the HCI community. As an additional contribution of our paper, we also aimed to illustrate in general the utility of acceleration as primary data when looking at movement quality. We believe that this is particularly relevant to the HCI field because of increasing use of accelerometers in mobile devices and proliferation of mobile applications that take advantage of acceleration-based data.

As perspectives of our study, we are currently applying the results of the evaluation of the EFFORTDETECT presented in this paper, to the iterative design and development of the system. We are experimenting with variations of the underlying recognition model by generating new types of training data while actively using movement expertise to inform the process. For instance, we initially trained the system with movement corresponding to the eight *BEAs*; we are pursuing this work by generating training data that correspond to qualities that interpolate between *BEAs*, e.g., movements that have qualities somewhere between Dab and Punch, or Slash and Wring. However, instead of controlling only the outer form of the expression by simply directing the dancer to move “slower” or “more lightly”, the dancer develops an inner image (such as “digging a shallow trench in the sand” or “closing a 6-foot high wooden gate”) that aids them in performing the movement. Our future work is being explored across each level of the data stream: sensor data acquisition, categorizing and modeling low-level motion features, iterating the movement recognition and analysis model, and multi-modal representation of movement recognition data.

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