Computational Laban Movement Analysis using probability calculus

Joerg Rett* Jorge Dias†

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Abstract

This work presents a system which implements the concept of Laban Movement Analysis (LMA) using probability calculus and Bayesian theory. Our Human-Interaction-Database (HID) provides sequences of position data from several persons performing several movements in 3-D (magnetic tracker) and 2-D (vision). From the position data a set of low-level features is calculated. Probability calculus is used to relate these low-level features and the frame of reference associated to the variables of LMA. The Bayesian theory provides the concept for calculation, learning and classification.

1 Introduction

When a person observes an actor performing a body movement he tries to anticipate the information the actor wants to convey. Analyzing the expressiveness of human movements has been under investigation for many centuries leading to several formalizations and concepts. Still, these concepts rely on humans analyzing other humans. Proving nowadays human-machine interfaces with a computational version of those concepts would be a big step toward socially interactive robots. For this the gap of a missing higher level cognitive systems that analyzes the observations need to be closed. One can think of the problem as a scenario where a robot is observing the movement of a human, analyzes the movement pattern and acts according to the extracted information (see fig. 1).

2 Laban Movement Analysis

Our approach is based on Laban Movement Analysis (LMA), which is a concept that provides descriptors for the static as well as for the dynamic content of human body movements [2].

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†Institute of Systems and Robotics E-mail:jorge@isr.uc.pt.

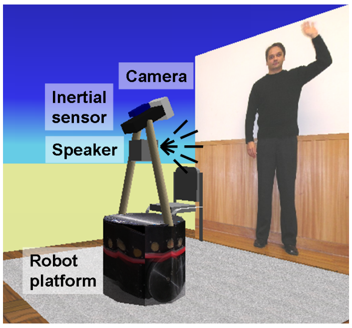


Figure 1: Nicole in position to interact.

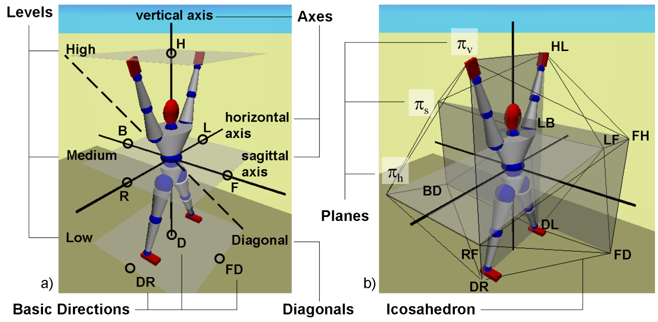


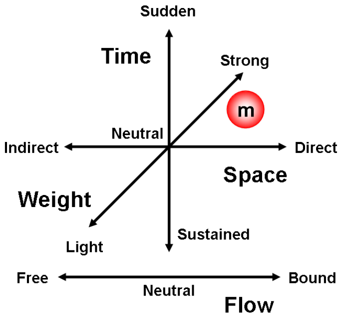
Figure 2: The concepts of a) Levels of Space, Basic Directions, Three Axes, and b) Three Planes and Icosahedron

The theory of LMA consists of several major components. *Space* treats the spatial extent of the mover's *Kinesphere* (often interpreted as reach-space) and what form is being revealed by the spatial pathways of the movement. Different entities are specified to express movements in a frame of reference determined by the body of the actor as shown in fig. 2. In [3] the concept of *Vector Symbols* was presented, which is based on lines of motion rather than points in space. One part of these *Vectors symbols* are movements parallel to one of the *Axes* and movements along lines that are equally stressed in all three dimensions (*Diagonals*) (see fig. 2.a). The *Space* component also defines three planes, i.e. the *Door Plane* π_v, the *Table plane* π_h, and the *Wheel Plane* π_s as shown in fig. 2.b). *Effort* deals with the dynamic qualities of the movement and the inner attitude towards using energy. It consists of four motion factors: *Space*, *Weight*, *Time*, and *Flow*. As each factor is bipolar and can have values between two extremities one can think of the *Effort* component as a 4-D space as shown in fig. 3.a. Prototypical movements where a certain *Effort*-value is predominant are presented in fig. 3.b.

3 Bayesian framework for LMA

The Bayesian framework enables us to model the dependencies between the low-level features and the descriptors of LMA. Bayesian nets show the dependencies in a graphical way using nodes and links. Probability calculus enables us to compute the probability distribution for the values of a variable given the sets of known and unknown variables. The definitions for propositions, variables, probabilities and their conjunctions can be found in annex A.

Figure 4 shows the Bayesian net of our system, representing the dependencies and thus, giving the possibility us to simplify the joint distribution. The nodes represent variables (e.g. movement M), the links describe the dependencies between the nodes. We have chosen



a)

b)

Effort	Movement
Space Direct	Pointing gesture
- Indirect	Waving away bugs
Weight Strong	Punching,
- Light	Dabbing paint on a canvas
Time Sudden	Swatting a fly
- Sustained	Stretching to yawn
Flow Bound	Moving in slow motion
- Free	Waving wildly

Figure 3: The bipolar *Effort* qualities: a) represented as a 4-D space containing a movement m, b) with their movement prototypes.

to start with the variables that exhibit the highest level of abstraction (i.e. M), calling it the *Concept Space*. Their child nodes are found in the *Laban Space* which holds the sets of variables concerned with *Effort* and *Space*. We have called the lowest level of abstraction *Physical Space* which holds the set of low level variables (i.e. K, Vel and Acc). The direction symbols (i.e. A, B and C) are both, a Laban concept and a low-level feature. Our system uses movement segmentation to get distinct *Effort* parameters for each segment (phase Ph) of the movement [6]. The *Space* component of LMA is modeled using the concept of vector symbols. Our direction symbols A, B and C are calculated from the direction of the displacement vector, one for each plane π_v, π_h and π_s, respectively. The *Effort* component of LMA models the dependencies between e.g. the *Time* $E.Ti$ and the velocity Vel variable. Table 1 in the annex will present all variables used in the model with their name, symbol and a short description. The variable values and their cardinality are shown in (6) from the annex. We can describe the joint distribution while omitting the conjunction symbol $\wedge$ as:

$$\begin{aligned}
& P(I\ M\ Ph\ E.Sp\ E.We\ E.Ti\ E.Fl\ A\ B\ C\ K\ Vel\ Acc) \\
= \ & P(I)\ P(M)\ P(Ph)\ P(E.Sp \mid M\ Ph)\ P(E.We \mid M\ Ph)\ P(E.Ti \mid M\ Ph) \\
& \quad P(E.Fl \mid M\ Ph)\ P(A \mid M\ I)\ P(B \mid M\ I); P(C \mid M\ I) \\
& \quad P(K \mid E.Sp\ E.We)\ P(Vel \mid E.Sp\ E.We\ E.Ti\ E.Fl)
\end{aligned} \tag{1}$$

Knowing that the variables are all discrete we can express conditional probability distributions (e.g. $P(A \mid M\ I)$ as tables. Learning is represented in our model through the process of filling all the conditional probability tables with values. The tables are filled by collecting all evidences for a given assumption and creating a probability distribution. In the case of $P(A \mid M\ I)$ a number of direction symbols $a_1, a_2, \ldots a_n$ is collected form n trials for a known movement $M = m$ and frame $I = i$. A distribution can be obtained by building a histogram. As this scheme requires a set of labeled data we may call it supervised learning.

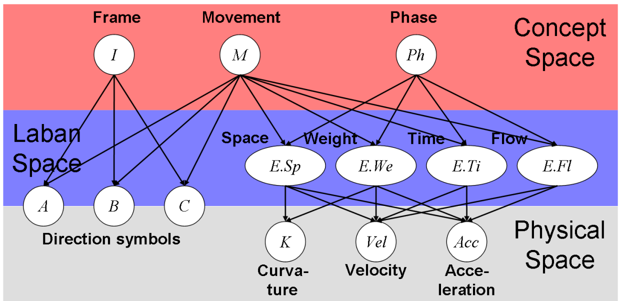


Figure 4: Bayes-Net of the LMA model.

Classification is the final step after the model has been established and the tables have been learned. Given our joint distribution $P(I\ M\ Ph\ E.Sp\ E.We\ E.Ti\ E.Fl\ A\ B\ C\ K\ Vel\ Acc)$ we need to formulate a question, i.e. what we want to classify and what we can observe. In our case we are interested to classify an unknown movement from the evidences observed in the *Physical Space*. In the following we continue with a simplified question, i.e. classifying a movement M taking into account only the direction symbols A and the frame I (2).

$$P(M \mid I\ A) = P(M)P(A \mid M\ I) \tag{2}$$

We can compute the *likelihood* of a sequence of n direction symbols by assuming that the observed direction symbols are independently and identically distributed (i.i.d.). The joint probability will be the product of the probabilities for each frame as shown in (3).

$$P(a_{1:n} \mid m\ i_{1:n}) = \prod_{j=1}^{n} P(a_j \mid m\ i_j) \tag{3}$$

The probability distribution of the movements M after observing $n+1$ direction symbols A can be formulate in a recursive way. Assuming that each frame I a new observed direction symbols arrives we can state and expressing the online behavior by (4).

$$P(M_{n+1} \mid i_{1:n+1}\ a_{1:n+1}) = P(M_n)\ P(a_{n+1} \mid M\ i_{n+1}) \tag{4}$$

The probability distribution of m for $n = 0$ is the *prior*. As a rule for classification we use the maximum a posteriori (MAP) method.

4 Implementation of LMA

We have created a database of human movements, called Human Interaction Database (HID) which is accessible through *WWW* [5]. The database consists of image sequences, high precision 3-D position data and results from our visual tracker and classifier. The HID is

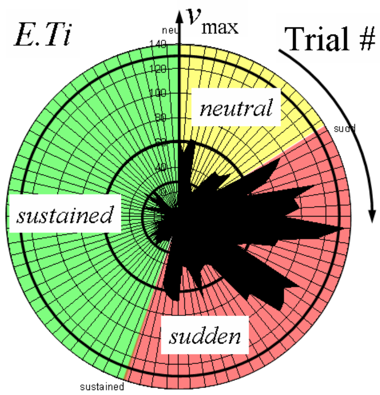


Figure 5: Evaluating maximum velocity v_{max} on several trials performing movements with known values for the Effort-Time variable.

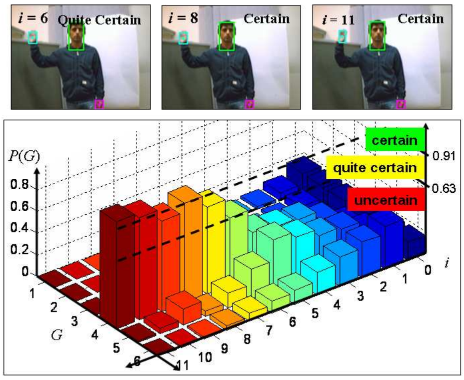


Figure 6: Evolution of the movement probabilities $P(M)$ along the time (i).

holds the movements suggested in fig. 3. The high precision 3-D position data is obtained from a 6-DoF magnetic tracker (Polhemus Liberty) with sensors attached to several body parts and objects. To collect the visual tracking data we use the gesture perception system (GP-System) [4] of our social robot Nicole. The tracking data consists of: i) the 2-D or 3-D position $\mathbf{X}_{bp}$ of a point belonging to a body part bp and ii) the timestamp t_i given by some timer function of the system. From the tracking data values for velocity, acceleration and curvature are calculated for each of the three planes π_v, π_h and π_s. To implement learning and classification we use the *Bayesian programming* methodology [1]. A *Bayesian Program* (BP) is a generic formalism to build probabilistic models and to solve decision and inference problems on these models. An example for a generic *Bayesian Program* is shown in fig. 7 in the annex.

5 Results

In the experiment to evaluate the importance of low-level features as evidences for the Laban parameters, 75 trials were performed, each represented by a sectors of the circle shown in fig. 5. It can be seen that most of the high (130 - 60) velocities can be found in the *sudden* sector. Similar is true for the medium velocities (60 - 30) and the *neutral* sector and also for the low velocities (30 - 0) and the *sustained* sector.

The evolution of the anticipated movements and the certainty of the belief is shown in fig. 6. It is an example of an performed *Bye-Bye* gesture. It shows which gesture the agent anticipates due to the highest probability and how certain he is about his guess.

6 Conclusion

This article gave an introduction to the framework of Laban Movement Analysis (LMA) emphasizing those entities that were expected to be useful for a computational representation. We presented the Bayesian models for computational LMA in form of Bayesian nets and joint distributions. A simplified model using the *Space* component of LMA to classify movements was chosen to present the concept of learning and classification. We presented our technical approach to track human movements (i.e. visual and magnetic) and store the output in our Human-Interaction Database (HID). We presented the set of low-level features calculated from the tracked data and the methodology of *Bayesian Programming*. The results indicated that there is a set of low-level features that can be used as evidences for the Laban parameters and that the classifier is able to make online-predictions, thus giving the system a sense of anticipation. In the application of socially assistive robots we are developing and then evaluating the feasibility of using our social robot Nicole for rehabilitation. We have ongoing work in the area of smart houses and environments to apply computational LMA to people tracking.

References

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Variable	Symb.	Description
Frame	I	index of the data frame
Movement	M	Type of movement, e.g. $M = pointing$
Phase	Ph	Temporal segment, e.g. $Ph = Rest$
Effort Space	$E.Sp$	e.g. $E.Sp = direct$
Effort Weight	$E.We$	e.g. $E.We = strong$
Effort Time	$E.Ti$	e.g. $E.Ti = sudden$
Effort Flow	$E.Fl$	e.g. $E.Fl = free$
Direct. Symb.	A, B, C	Vector Symbols (Atoms) in π_v, π_h, π_s
Curvature	K	Change of displacement angles
Speed	Vel	Velocity level, e.g. $Vel = low$
Speed Gain	Acc	Acceleration level, e.g. $Acc = high$

Table 1: Global variables

A Annex

A logical proposition can be either true or false. The conjunction of propositions a and b is denoted $a \wedge b$ the negation of proposition a by $\neg a$. Variables are denoted by names starting with one uppercase letter. A discrete variable X is a set of logical propositions x_i which means that the variable X takes its ith value. $\langle X \rangle$ denotes the cardinal of the set X. To be able to deal with uncertainty, we attach probabilities to propositions. To each proposition a a unique real value P(a) in the interval [0, 1] is assigned. The probability of conjunctions of propositions is denoted by $P(a \wedge b)$. The probability of a proposition a conditioned by some other proposition b is denoted by $P(a|b)$. The conjunction rule (5) gives the probability of a conjunction of propositions.

$$P(a|b) = P(a) \times P(b|a) = P(b) \times P(a|b) \tag{5}$$

All variables used in the model are presented in table 1.

$$
\text{Program}\begin{cases}
\text{Description}\begin{cases}
\text{Specification}\begin{cases}
\text{Relevant variables:}\\
X_l,\ X_2,\ \ldots\ X_N\\
\text{Decomposition:}\\
P(X_1 \wedge X_2 \wedge\ \ldots\ \wedge X_N =\\
\quad P(L_0) \times P(L_1|R_1)\ \ldots\ \times P(L_K|R_K)\\
\text{Parametric forms:}\\
P(L_0)\text{: type of distribution or question to an other BP;}\\
P(L_1|R_1)\text{: type of distr. or question to an other BP;}\\
P(L_2|R_2)\text{: type of distr. or question to an other BP;}\\
\ldots\\
P(L_K|R_K)\text{: type of distr. or question to an other BP;}
\end{cases}\\
\text{Identification:}\\
\text{Learning the free parameters of the parametric forms.}
\end{cases}\\
\text{Questions:}\\
P(Search|known)
\end{cases}
$$

Figure 7: Generic Bayesian Program.

Variables of the *Laban Space* and *Physical Space* with their values and cardinality.

$$
\begin{aligned}
E.Sp &\in \{direct, neutral, indirect\}\ \langle 3\rangle\\
E.Ti &\in \{sudden, neutral, sustained\}\ \langle 3\rangle\\
E.We &\in \{strong, neutral, light\}\ \langle 3\rangle\\
E.Fl &\in \{bound, neutral, free\}\ \langle 3\rangle\\
A &\in \{O, U, UR, R, DR, D, DL, L, UL\}\ \langle 9\rangle\\
B &\in \{O, F, FR, R, BR, B, BL, L, LF\}\ \langle 9\rangle\\
C &\in \{O, U, UF, F, DF, D, DB, B, UB\}\ \langle 9\rangle\\
Vel &\in \{rest, slow, medium, fast\}\ \langle 4\rangle\\
Acc &\in \{zero, low, medium, high\}\ \langle 4\rangle\\
K &\in \{180, 135, 90, 45, 0, -45, -90, -135\}\ \langle 8\rangle
\end{aligned}
\tag{6}
$$

An example for a generic *Bayesian Program*.