HIERARCHY AND REVERSIBILITY IN HUMAN MOTION MODELLING
- A BAYESIAN APPROACH -

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Abstract. Human-Machine Interaction (HMI) relies on the capability of an artificial system to analyse a given signal input, and react accordingly. A growing trend on HMI, is to develop interfaces that are more human-like, such as smart spaces or interfaces for companion robots. Such growing complexity is leading scientific research to develop systems yielding a better perception of human communication streams and provide responses resembling human-behaviors.
This paper presents a probabilistic framework that allow artificial systems the capability to automatically characterize human motion. We propose a model to perform Analysis and Synthesis of body part motion, from and into trajectory signals respectively. As a conceptual support to its taxonomy, the model is based on a theoretical conception of human motion, *Laban Movement Analysis*. The developed model targets some key characteristics: *reversibility*, *scalability* and deal with phenomenon *uncertainty*. Bayesian Methods represented as their equivalent Dynamic Bayesian Network allow us to explore such characteristics. To address the specific problem of reversibility, we explore a possible solution: Bayes theorem symmetry property in the context of model hierarchy based on a dictionary approach.
The quality of generated features plays an important role in model conception stage and reflects with great impact in the actual model performance. To address this problem, we use a method to select a feature subset, quantifying and comparing their discriminating efficiency across the classes of the model's variables.
The application opportunities are transversal, where motion evaluation has potential application in a wide range of scientific areas such as surveillance, sports performance analysis or physiotherapy.

Keywords: Laban Movement Analysis, Dynamic Bayesian Networks, Model Reversibility, Hierarchic Taxonomy, Human-Machine Interaction.

1 Introduction

A leading trend in Human-Machine Interaction research is developing artificial systems that can perceive a wide range of human communicating streams, from verbal to non-verbal cues.

Appart from enhancing their interpretation capabilities, interfaces are also improving to become more human-like, e.g. companion robots. These systems reactions are still very 'mechanical', whereas research is converging to pursuit responses that resemble the way a person performs.

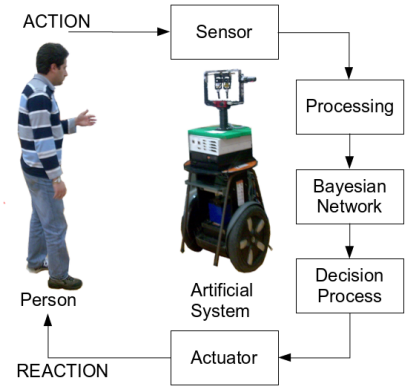


Fig. 1: Human-Machine Interaction Model.

Within such research context, this article presents a probabilistic model to characterize human motion, applying Bayesian Methods, more precisely, Dynamic Bayesian Networks (DBN).

Encompassing the ability to analyse motion from body part trajectories, we formulate a model exploiting Bayesian symmetry to perform the **Reverse** problem, synthesis. The goal is to provide data through Bayesian inference, that will allow estimating a trajectory for each body part, rather than dealing with the complexity involved with the Inverse Kinematics problem.

Taking into consideration the interpretation capabilities of different entities, the model is developed over an **Hierarchic** taxonomy, where each layer represents a different interpretation level.

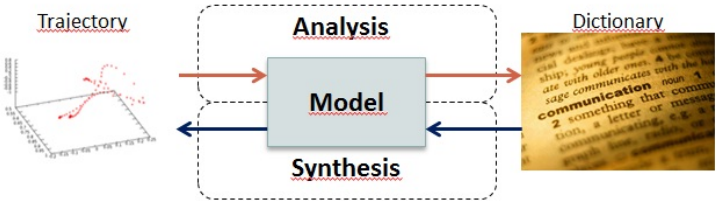


Fig. 2: Simplified block diagram for the proposed approach, yielding the reversible model and the input/output pair.

Represented in Figure 2 is a simplified overview of the proposed model approach.

Body part trajectories are on one end of the input/output pair. Trajectory works well as an observable signal to generate a given interpretation. Moreover it can easily be applied to mechanical or virtual systems to generate motion (e.g. reverse kinematics).

On the other end, a multilayer **Dictionary** defines an intuitive and comprehensive syntax based on a theoretical movement notation. Laban Movement

Analysis (LMA) [1–3] is currently one of the most applied systems to analyse human motion, used as a tool by dancers, athletes, physical and occupational therapists. Divided into kinematic and non-kinematic component categories[1], LMA defines two semantic levels for motion characterization [3].

Not being the core of this work, we advise reading Anne Hutchinson-Guest's work [4] for further information about several motion notation systems.

The model is **Scalable**, allowing adding new variables and/or sub-models, becoming fair to state that different phenomena require different modelling methodologies (**Flexibility**). However, sub-models should have equivalent representations as DBNs [5]. Moreover, from a computational perspective, inference methods that could not be applied originally, are now applicable.

To validate these properties, we extend our original model (motion characterization) with a 3^{rd} level.

To establish dependencies between variable nodes we use Feature Selection Toolbox (FST) [6] to measure feature performance regarding the task of discriminating between variable classes. Selecting the best features, explicitly establishes the conditional Bayesian dependencies.

1.1 Related Work

Hongeng et al. [7] presented a new method to recognize human activities. Their work represents individual and interactive activities as a composition of events. The model is an hierarchical representation of activities [8], where events are organized in levels of abstraction, allowing flexibility and modularity.

In 2005, Arsic et al. [9] proposed a system to automatically detect abnormal behaviour from observing actions performed by upper body. Arsic postulated that behaviours like nervous or aggressive could be described as a combination of simple activities, performed by different body parts.

In 2009 Swaminathan et al. [10] proposed a model to analyse Laban Shape Quality, incorporating it into a mixed-reality environment with applications to kinesiology training Modelling Shape in Dynamic Bayesian Networks, they fused movement features (Directional Vectors) across body and time.

Park and Aggarwal [11] proposed an event hierarchy based approach to a semantic-level Analysis of Human actions, using three levels of abstraction, modelled using independent different Bayesian methodologies. The semantic grammar was based on geometric descriptors of Body parts.

Combining trajectory based detection and body-based estimation to analyse pick-up and drop-off events, was proposed by Lao et al. [12]. Estimating the pose and segmenting moving objects from images allowed a classification function to discriminate between the event space.

Du et al. [13] proposed a model to recognize interaction activities. Applying Dynamic Bayesian Networks, features emerging from trajectory and object recognition are used to classify between 5 different basic activities.

[1] Literature is not consensual about the number of components. Some authors defend the existence of a 5^{th} component, Relationship, which is more focused on interaction and how the other 4 components relate, being however the least studied component.

Recently, Kwon et al. [14] presented a work in motion analysis and synthesis using a specific motion vocabulary applied to fighting sports. Bayesian methodology is applied to an analysis and a synthesis model separately. The synthesis problem, focuses on identifying a one of a predetermined set of sequential basic motions.

A Bayesian Network approach, using physical features to modelling Laban Movement Analysis in the context of Human-Robot Interaction has been investigated by Rett in his Ph.D. thesis [2]. Rett gave a first step on demonstrating how LMA could be applied to classify a small set of different movements.

2 Input Signal

The developed models aim device independency, i.e. the generated features should abstract themselves from the acquiring device.

In order to enforce abstraction, all data is considered egocentric. Projective geometry [15] is used to map device related data into an egocentric referential.

The data was acquired using *Mvn suit* from *Xsens Technologies*. At a rate of $1Hz$, each feature vector is generated from a set of trajectory points $P_i(x, y, z)$ sampled at frequency of $36Hz$. We explicitly assure density homogeneity across all cluster samples.

2.1 Feature Generation Methodologies

Santos L. et al. [16] investigated the performance of different feature generating methods regarding the qualitative meaning of Laban Movement Analysis semantics. To evaluate the algorithms, Santos L. measured class separability using a methodology based on Scatter Matrices [17].

Within Feature Generation, [16] identifies some dominant methodology domains. Testing 4 algorithms considered to cover those domains, results lead to the selection of the Karhunen-Love Transform (KLT) [18]. The Discrete Fourier Transform [19], Local Linear Embedding [17] and the 7 Moments of Hu [17] where other evaluated algorithms.

The Karhunen-Love (KL) transformation matrix exploits statistical information describing the data, whose symmetric properties generate a set of mutually orthogonal eigenvectors Ve. The vectors $Ve_i = (x_i, y_i, z_i)\ , i = 1, 2, 3$ encompass the principal directions of the spanned data, whilst variance on each direction is given by correspondent eigenvalues $v_i\ , i = 1, 2, 3$.

$$\text{KLV} = [v_1\ v_2\ v_3\ x_1\ y_1\ z_1\ x_2\ y_2\ z_2\ x_3\ y_3\ z_3] \tag{1}$$

In order to determine the subset of features $V \subset KLV$ better characterizing each Laban variable, we exploit Feature Selection Toolbox.

2.2 Feature Selection Toolbox

Feature Selection Toolbox (FST) is *"A software package developed for the purpose of feature selection in statistical pattern recognition (...) includes (...) methods suitable for dimensionality reduction, classification and data representation."* [6].

Methodologies thorough description is out of the scope of this work, however we refer the reader to some known works [6, 17, 20].

Although a recent version exists (FST3), we find suffice to use FST1, whose lattest version is dated 2002. Its most interesting feature to this work, still uses up to date methodologies (discriminating ratio measures).

An overview of the search strategies for feature selection which are used in FST1 is presented. For further details, the reader should address Somol et al. work [6] or FST webpage [21].

The primary goal is to find an optimal subset of features that maximize and adopted discretization criterion. These usually are probabilistic inter-class distance measures. Some implemented methods are Battacharyya distance, Mahalanobis Distance, Generalized Mahalanobis, Fisher Discriminant Ratio and Divergence, however allowing using external measuring functions.

Somol et al. state that methods to select a subset maximizing a given criterion, can be divided in optimal and sub-optimal. The universal optimal method is exhaustive search, however intractable for high dimensional problems. Branch and Bound (BB) algorithms appear as the only viable solution to exhaustive methods.

FST1 provides both methods: exhaustive and BB. Basic (BBB), Enhanced (EBB), Fast (FBB) and Branch and Bound with Fast Prediction (BBFP) are the BB algorithms available.

Sub-optimal methods do not guarantee optimal results, but are able to provide optimal or at least near-optimal in most cases. Some available sub-optimal algorithms available are Sequential Forward Search (SFS), plus-L-minus-R, floating sand adaptive floating search methods and oscillating search methods.

In case overmentioned algorithms fail to provide reasonable results, FST also provides approximation model based methods. This approach is based on approximating unknown probability density functions by finite mixtures of a special product type. These are different but rather powerful methods to approach dimensionality reduction. Results achieved with the previous methodologies are reasonable from our point of view, even though, we found useful to mention these.

2.3 Results

To select the optimal sub-set $V \subset KLV$ from the available features, we used FST1 to sort the 12 features based on their discriminative ratio. Table 1 presents the first 6 ranked features. From the ranked set, we explicitly define the model's dependencies between features and Laban variables.

Table 1: Feature Ranking Table using Mahalanobis Criterion with Enhanced Branch and Bound.

	RANK					
	1	2	3	4	5	6
EfTime	v_1	z_1	x_2	y_2	z_2	x_3
EfSpace	v_1	x_1	y_1	z_2	x_3	y_3
EfWeight	y_1	x_2	y_2	x_3	y_3	z_3
EfFlow	v_1	y_1	x_2	x_3	y_3	z_3
ShFlow	v_1	v_3	z_1	x_2	y_3	z_3
ShSpace	v_2	x_1	z_1	z_2	y_3	z_3

Criterion absolute values are omitted for simplification, however for the lower ranked half, the criterion absolute values are low, meaning they have no relevant discriminative properties. Also, results show features ranking 5^{th} and 6^{th} are similar across all variables. Given that fact, we decided to select the first 4 features to define model dependencies. Taking as an example variable '*Eftime*' we explicitly define it as dependent on v_1, z_1, x_2 and y_2, yielding $P(EfTime|v_1 \cap z_1 \cap x_2 \cap y_2)$. Model formulation is addressed in detail in the next section.

3 Model development: A Bayesian approach

3.1 Global Model

Exhibiting a hierarchical structure, the global model is decomposed hierarchically organized submodels.

Let us assume π as the sub-model space. At level j, there is one sub-model ${}^j\pi_k$ for each variable k (cardinality of k is not necessarily equal across all levels j).

Let V be the variable set of the model, and ${}^jV_k \in \{V\}$ the variable k at a given level j of the global model. At level j, a sub-model k is generally formulated as

$$P(V|[\pi =^j \pi_k]) = P({}^jV_k)P({}^{j-1}V_{k'}|{}^jV_k) \tag{2}$$

which establishes variable dependencies, based on Bayes Theorem, across subsequent levels $j-1$ and j.

Further expanding the formulation, assume two subsequent levels, here numbered $j=1$ and $j=2$ for simplicity purposes, encompassing f and l variables, respectively ${}^1V_{1:f}$ and ${}^2V_{1:l}$. We assume variables ${}^jV_i$ to be independent and identically distributed.

Given $j=2$, each variable $i=1:l$ sub-model yields

$$P({}^2V_i|{}^1V_1 \cap ... \cap \ {}^1V_f) = \frac{P({}^2V_i)\ \Pi_{q=1:f} P({}^1V_q|{}^2V_i)}{P({}^1V_1 \cap ... \cap \ {}^1V_f)} \tag{3}$$

which develops into the following proportionality

$$P({}^2V_i|{}^1V_1 \cap ... \cap \ {}^1V_f) \ \propto \ P({}^2V_i)\ \Pi_{q=1:f} P({}^1V_q|{}^2V_i) \tag{4}$$

Table 2: Possible states for the defined variables in Laban Space.

Variable	Space State
EfTi	Sudden, Sustained
EfSp	Direct, Indirect
EfFl	Free, Bound
ShFl	Spreading, Enclosing
ShSp	Sinking, Rising

3.2 Variable Space

Let $j = \{1, 2, 3\}$ define the different levels, whose level $j = 3$ purpose is to demonstrate the properties Scalability and Flexibility. From this point on, we denote variable spaces ${}^1V_i$, ${}^2V_i$ and ${}^3V_i$ as F_i, L_i and M_i respectively (acronyms for **F**eature, **L**aban and **M**ovement Space States).

Hierarchy is implicit when applying Bayesian methodology, but we enforce this taxonomy by superimposing Laban (LMA) concept onto our network to explicitly define a *Hierarchic Dictionary*.

This concept is a consequence of defining a Variable and Space state for each hierarchic level F, L and M.

Based on fundamentals of LMA and Labanotation, variable states at level j will combine themselves defining an increasingly complex semantic states at level $j + 1$. This process is reversible.

Observation Space ($j = 1$): According to subsection 2.1 and results from subsection 2.3, let F be the Feature Space.

$$F_i \in \{F\} \; where \; F_i \in \mathbb{R} \; \forall \; i = 1 : f \tag{5}$$

Variables F_i relate directly to equation (1).The Observation Space is not reduced to the proposed features, whereas it is possible to expand F to embrace others.

Laban Space ($j = 2$): In Laban Space we represent Laban Movement Analysis components of interest as variables. We represent three (Time, Space, and Flow) of the four Effort qualities, and two Shape component qualities (Flow and Space). Table 2 shows the binary states for each variable in Laban Space.

$$L \in \{EfTi, EfSp, EfFl, ShFl, ShSp\} \tag{6}$$

Movement Space ($j = 3$): To demonstrate the model Hierarchy and Scalability, a 3^{rd} level on top of the existing hierarchic model was implemented. Inspired in Hutchinson's work [3] we defined a variable M belonging to Variable Space ${}^3V_i$. This variable defines a set o possible Movement states.

$$M \in \; \{Lift, Punch, Bye, Write, Point\} \tag{7}$$

Each of the presented movements exhibits a different sequence of states as described in Table 2.

3.3 Model Formulation

Let us introduce the global model represented as a Directed Graph. Figure 3 illustrates the defined sub-model spaces π, their variable sets F,L and M and the inter-level dependencies. Observation Space denoted ${}^1\pi_f$, as the the designation suggests, constitute the set of observable (hard) evidences. As defined, there are $i = 1 : f$ independent observable variables F_i which can are represented as in equation (5).

Regarding Laban Space (${}^2\pi_l$) we assume that each Variable reflects the behavior of the observed data cluster generating the features. Thus, we define each Laban Component L_l dependent of the observed feature values, which analogously to equation (4) yields for each Laban variable L_l.

$$P(L_l|F_1 \cap ... \cap F_f) \propto P(L_l)\ \Pi_{q=1:f} P(F_q|L_l) \quad (8)$$

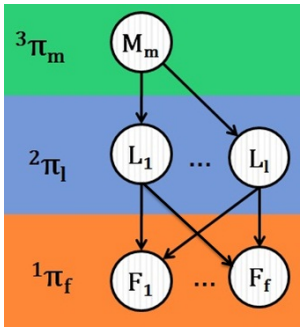


Fig. 3: Directed Graph representation, yielding the variable sets F,L and M for each of the hierarchic levels.

Flexibility & Scalability

Level ${}^3\pi_m$ aims to demonstrate the properties of Flexibility and Scalability of the model. The model is scalable to any given j additional semantic levels. Laban theory states the possibility to divide a movement into a sequence of simpler actions (Laban Components). To model sequences, one very popular methodology is Markov Models. Markov models belong to the Bayesian family of algorithms, and have equivalent representation as Dynamic Bayesian Networks.

Let Ω_M be the finite set of possible states for Variable M, and Ω_L the finite set of possible Observations, corresponding to the Laban Component States. Assume M_t the state of variable M and L_t the state of variable L, both at time t. The initial state distribution is given by $\pi = \{\pi_i\}$ with $\pi_i = P(M_0 = q_i)$. Transition and Observation probabilities are given by $A = \{a_i j\}$ and $B = \{b_i\}$ respectively, corresponding to $P(M_{t+1} = q_j|M_t = q_i)$ and $P(M_t = v_k|M_t = q_i\ t)$.

Formulating our Markov Model as a Bayesian Network will yield

$$mi_t(i,j) = P(M_t = q_i, M_{t+1} = q_j|\sigma A\ B\ \pi) \quad (9)$$

where σ corresponds to the sequence of actual observations $l_1, \ldots, l_T$. Given the causality in our graph model, the observation set corresponds to the variable space state depicted in equation (6), formulated upon (8).

3.4 Inference: Learning

Regarding the probabilistic characterization model ${}^2\pi_l$, we assume all $F_f \in \{F\}$ are probabilistically independent and identically distributed. The same assumption is made for all variable set L.

Three-dimensional trajectories are acquired are a rate of $36Hz$. We segment the trajectory, generating a data cluster at time intervals of $\Delta t = 1s$. Each trajectory will be segmented into P_n cluster with $n = 1, ..., w$. Given the specified acquisition rate and Δ_t, each cluster has 36 point coordinates.

Each set P_n will generate a set of feature ${}^nF_f$ values[2] according to the established in Section 2.

Each cluster set is manually labelled with specific Laban attributes as illustrated in Figure 4.

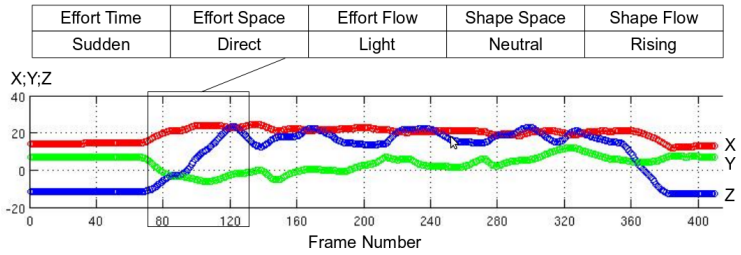


Fig. 4: Example of manual notation for sample interval $\in [80, 120]$.

Collecting all samples P sharing the same state, across all movements, we compute the average value for each feature F_f.

$$\mu_i = \frac{1}{w} \Sigma_{q=1:w} F_q \tag{10}$$

and the standard deviation

$$\sigma_i = \sqrt{\frac{1}{w} \Sigma_{q=1:w} (F_q - \mu_i)^2} \tag{11}$$

Hence, we represent the probability of a feature F_f given the knowledge of the component L_l state asthe Gaussian Distribution (Figure 5).

$$P(F_f | L_l) = N(\mu_f, \sigma_f) \tag{12}$$

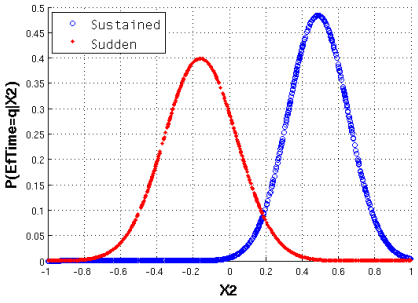


Fig. 5: Example of learned distribution for variable Effort Time and Feature x_2.

To the submodel ${}^3\pi_m$, we have represented the Markov Model as a Bayesian Network, thus we can apply standard Bayesian Network Inference Algorithms. Given the parametrization of the model presented in equation (9), we can apply the classical *Maximum A Posteriori* approach for inference.

[2] The superscript n, in this particular case symbolizes the value of feature F_f for a given set P_n.

3.5 Reversibility

Given a combination of Laban States, we aim to generate a probabilistic space from which is possible to fit a synthesized trajectory. To achieve such representation, we explore Bayes Symmetry Property. Assume our ability to estimate a particular state S for a component L_l given the knowledge of features F_f (see equation (8)) . Reversing the arcs in the Directed Graph, we want to estimate the value for each feature F_f given the knowledge of components L_l states.

$$P(F_f|L_1 \cap ... \cap L_l) \ \propto \ P(F_f) \ \Pi_{q=1:l} P(L_q|F_f) \tag{13}$$

However, we have no information about $P(L_l|F_f)$. Rather from the learning stage, we have knowledge of the distributions $P(F_f|L_l)$. Bayes Theorem states that

$$P(L_q|F_f) = \frac{P(L_q)P(F_f|L_q)}{P(F_f)} \tag{14}$$

hence, replacing (14) in (13) yields

$$P(F_f|L_1 \cap ... \cap L_l) \ \propto \ P(F_f) \ \Pi_{q=1:l} \frac{P(L_q)P(F_f|L_q)}{P(F_f)} \tag{15}$$

which assuming the prior $P(L_q)$ as uniform, will yield, upon simplification

$$P(F_f|L_1 \cap ... \cap L_l) \ \propto \ \Pi_{q:1:l} P(F_f|L_q) \tag{16}$$

Thus, given $P(F_f|L_l)$, it is possible estimate the most probable values for a given feature F_f from the linear product. The resulting features define an ellipsoid in the Cartesian space, where the eigenvectors define the orthogonal orientations of the ellipsoid and eigenvalues, the variance along each of the axis, representing a probabilistic cluster trajectory space.

4 Experimental Results

According to our motivation, we aim to give the artificial system the capability to analyse human motion, using the semantically rich lexicon provided by LMA notation. The experimental database encompasses 5 different actions: lifting and object, waving bye-bye, writing the name on a wall, punching and pointing. The actions have on average, 20 performances, divided between 3 to 5 different authors. Hence, we present Table 3 with the classification results for sub-model ${}^2\pi_i$, measuring our models capability in generating an automatic symbolic description for the observed human motion (Figure 6 illustrates and example of a human motion). The acronym C.R. stands for positive Classification Results, which exhibit the percentage of correctly classified variable states. Results demonstrate that the classifier does not behave regularly across all variables. The justification is twofold. First, we argue the cluster size for sampling may not be ideal. When

Table 3: Submodel ${}^2\pi_i$ table, yielding the results for positive classification of LMA characteristics $P(L_l|F_f)$.

	Sudd	Sust	Dir	Ind	Free	Bound	Rise	Sink	Spr	Encl
C.R.	45.61%	95.97%	89.88%	77.30%	96.20%	60.12%	23.61%	89.47%	67.89%	31.82%

Fig. 6: Some frames of a 'bye-bye' performance and the classification evolution.

notating, a cluster may not share the selected notated state across the time window, introducing noise and affecting feature generation. Secondly, despite suiting some variables, KLT might not be ideal for the whole set. An additional aspect possibly affecting results is 'prior' distribution, considered uniform. A better definition of this distribution can improve the model. Justifying this strategy is the assumption that at a given time, a Laban state is independent of prior observations, e.g. a movement that is being sustained at one instant, is not necessarily sustained in the next instant. The unregular classificative behavior for sub-model ${}^2\pi_i$ will reflect in sub-model ${}^3\pi_i$, given their explicit dependency. The model will now use the symbolic representation of human motion to generate high level interpretation. In fact, prior to decide its reactive behavior, we find useful for the system to have a more descriptive knowledge of the observed actions. Our model presents a top level $j = 3$ allowing identifying between a set of possible movements (See Table 4). Taking into consideration the impact of the

Table 4: Submodel ${}^3\pi_i$ table, yielding the results for positive Movement classification $P(M_m|L_l)$.

	Lift	Write	Punch	Point	ByeBye
C.R.	91.23%	56.30%	78.5%	58.00%	51.78%

previous sub-model results, and the geometrical similarity between pairs Write

Table 5: Comparison between learned and estimated Gaussian parameters for different number of combined variables. Features are on left column and regard variable "Effort Time" for state "Sudden".

	Number of variables combined with 'Effort Time'							
	5		4		3		Learned	
Sudden	AGV	SD	AGV	SD	AGV	SD	AGV	SD
v_1	32.4895	11.3777	33.9622	12.2962	35.9711	12.7599	46.5255	18.5112
z_1	0.5260	0.1103	0.5101	0.1084	0.4881	0.1051	0.2346	0.4294
x_2	0.5205	0.0682	0.5152	0.0713	0.5086	0.0735	0.4885	0.1652
y_2	0.3316	0.0188	0.3335	0.0199	0.3362	0.0211	0.3606	0.1530

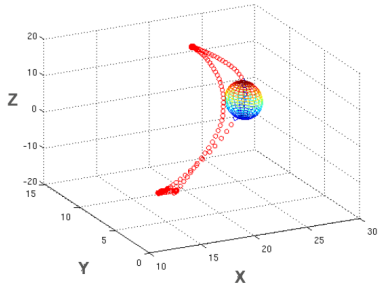
- ByeBye and Punch - Point, we consider results for movement classification to be acceptable.

Exploring reversibility to generate a probabilistic space, from which it is possible to synthesize trajectories to apply in virtual interfaces (Figure 7b). The probabilistic space is represented by a set of ellipsoids emerging from the synthesized KLF vector. Given the wide range of Laban combinations, avoiding a cumbersome load of tables[3], we present a standard format for the most prominent feature variables in Table 5. The number of combined variables has no relevant effect. The average computed value for v_1, being different from the learned, fits within its standard deviation. In the case of z_1, computed values are also different from learned ones. However, synthesized SD's are narrow opposite to the learned ones, which indicate that they fit the range. However, as stated in the analysis results, a better tune in features and notation might lead to better results. Figure 7a presents a possible application of synthesis. The graphical representation of the synthesized of vector superimposed over the ground-truth trajectory, allowing demonstrating a synthesized trajectory space can generate a signal similar to observed human trajectory. Analysing the complet set of results, we observed that the synthesized eigenvalues presented the biggest offset to their learned pairs. As for eigenvectors, with exception of values for z_1 and y_3, other coordinates values approach.

5 Discussion & Future Work

The current work presents a probabilistic model to characterize human motion based on a theoretical human motion notation system, Laban Movement Analysis. Analysis results are considered satisfatory, however, some issues need to be addressed in our upcoming research. We used a public toolbox, Feature Selection Toolbox presenting a methodology to select model dependencies. Exploring Bayes Symmetry Property to perform synthesis, we presented results for synthesized feature vector, generating a probabilistic trajectory with application to our virtual interface. Extending our model using a different Bayesian

[3] The computation was done for all features and all possible variable combinations.



(a) Synthesized probabilistic trajectory space, superimposed over the ground-truth signal.

(b) Example of a synthesized 'point' movement in an smart space.

Fig. 7: Synthesis illustration and application.

method, through is equivalent representation as Dynamic Bayesian Network, we demonstrate scalability. The space state for all models, defined an Hierarchic Dictionary, divided in a complex growing semantics inspired in Labanotation.

In upcomming research we aim to study the possibility of using a frequency filter to model the input abstraction. We will formulate the reverse model to an abstract hierarchic levels, taking into consideration the use of different Bayesian methodologies. The database will be extended into a comprehensive list of scenarios, annotated with Labanotation, encompassing single or interactive motions and made public. We aim to finalize the trajectory synthesis process generating a prototype smart space platform.

Acknowledgments

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