Parameterizing Interpersonal Behaviour with Laban Movement Analysis

– A Bayesian Approach -

Kamrad Khoshhal Roudposhti, Luís Santos, Hadi Aliakbarpour, Jorge Dias
Institute of Systems and Robotics, Department of Electrical and Computer Engineering, University of Coimbra
{kamrad, luis, hadi, jorge@isr.uc.pt}

***Abstract*—In this paper we propose a probabilistic model to parameterize human interactive behaviour from human motion. To Support the model taxonomy, we use Laban Movement Analysis (LMA), proposed by Rudolph Laban [11], to characterize human non-verbal communication. In interpersonal communication, body motion carries a lot of meaningful information, useful to analyse group dynamic behaviors in a wide range of social scenarios (e.g. behaviour analysis of human interpersonal activities and surveillance system). Taking the advantage of interpretation of social signals defined by Alex Pentland [19], and the descriptive body movement analysis proposed by Laban, we identified characteristics allowing both works to complement each other. To explore in group dynamics, we attempt to show the existent connections between Pentland's descriptions for Interpersonal Behaviours (IBs), and LMA parameters for human body part motions. Those relations are the keys to characterize the interpersonal communication. Given the uncertainty of the phenomenon, Bayesian's methodology is applied. The results present LMA parameters as reliable indicators for IBs, allowing us to generalize the model.**

I. Introduction

A recent research trend is trying to analyse complex human activity, which usually appear under social contexts, which is named Interpersonal Behaviour (IB). This work proposes a model to parametrize a set of IB characteristics using a body movement descriptor, Laban Movement Analysis (LMA) [11], by formulating the model under a Bayesian Network (BN) formalism (Fig. 1).

In society, people interact and influence each other, generating a number of complex dynamic processes (such as social roles, relationships, etc.) which happen when interacting. Human communication's analysis have been studied by psychologists for decades, and they believed that there is a meaningful connection between nonverbal signals and social interactions [26]. In [9], studying of groups was named group dynamics is related to psychology, sociology, and communication studies. In the fields, a group is commonly defined as more than one individual who is connected with others by social relationships.

LMA provides a language and vocabulary for interpreting body movement, which is useful to extract features from complex human movements such as interpersonal activities [15]. To analyse group dynamics, Pentland [19] presents several definitions for IBs which allow to enhance the existent connections between psychology and artificial intelligence science. Certainly there are many groups investigating group dynamics in psychology, but the Pentland's recent investigation is probably the first noticeable work which attempts to analyse the IBs, relating both sciences.

In the last decade, several approaches have been proposed to analyse human behaviour using different types of input

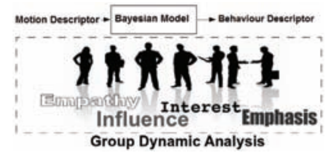


Figure 1. Proposed approach for interpersonal behaviour understanding

signals emerging from human nonverbal channels: facial expression, voice and body motion [17]. This research focuses just on 3D body motion-based signals as a part of nonverbal signals to analyse IBs. The related works more rely on voice and facial expression features, but the contribution of this work is to explore through different features belong to just body parts motions to analyse IBs. Based on the Pentland's methodology, a generalizable model defined for performed IBs, using Laban components, which are obtained from body motion-based low level features, as input features in the BN.

A. Related Works

Nowadays human behaviour analysis is a big challenge in different fields specially in social aspect. Social signals which come out of a group, are very important key in social science and surveillance systems in many applications like decision making and analyzing social behaviours which is core of social intelligence [27]. For the first time, Pentland's group [19] proposed social signal processing for different applications like; salary negotiations and hiring interview. A few groups are researching about social behavior analysis using different types of sensor data, in different scenarios such as small group interactions, roles recognition (in broad cast material and small scale meeting), and user interest sensing in computer characters. In [27], a couple of works related to each of these categories can be found.

The behaviours or social signals can appear from different kind of features which can be generally categorized in three parts; facial expression, voice and body motion [17]. Analyzing human motion is a prerequisite for understanding of human activities, such as human-robot and human-human interaction. Analysis of human activities can be investigated in different levels. Bobick in [5] presented a survey about the different levels of human motion definitions, such as human movement, activity and action. In Bobick's terminology, the movements are the lowest level of human motions which do not need any contextual or previous knowledge to be identified, but to understand human action or behaviour we need to have a sequence of human movements, related to the scenario. Several surveys about human motion-based analysis issue such as [1], [6], [10], [18], [16], [28], [20] were

978-1-4673-1612-5/12/$31.00 ©2012 IEEE

published. As can be realized from those previous works, analyzing IBs based on human body motion is less explored.

BN presents many advantages on using prior knowledge and modeling the dynamic dependencies between parameters of object states. In related fields, this approach is popular and researchers have been keen on applying it, such as Rett [21], who applied a general BN framework for analyzing human motions, and Ryoo and Aggarwal [22], who presented a framework for human action modeling by using BN for analyzing human activities. There are several reasons to use a Bayesian approach in our application: Bayes theorem is valid in all common interpretations of probability, can represent and solve decision problems under uncertainty, is a common approach to predict, an explicit approach to follow states, does not need a large amounts of data to be trained, and it is able to fuse different types of data in one model [13].

Pentland's group in [19] presented an interesting work to analyze IBs in different context like classroom, casino, etc. and defined several features as *Honest signals* and measured them by a mechanism namely, Sociometer. Then a number of social roles was defined by combination of those signals. Recently a few works have been proposed in this direction, for example; simple body motion-based and speech-based features are used in [7], and silhouette motion-based features are used in [24], for the mentioned purpose. A brief survey about social signal analysis was published in [27].

The state-of-the-art shows that there are several works which have been done in simple human motions activities and behaviours, but still there is a big gap between body motions and IBs context applications. These kinds of applications, when you just rely on body motions, are very valuable in many applications such as surveillance systems, but less explored. Thus, in this work, based on the pentland's definitions to estimate the different social signals or behaviors, an approach is proposed to obtain them by using just body motion-based features which is less explored and can be achieved by LMA descriptor [11], [29]. The main contribution of this work is presenting a new approach to parameterize IBs using LMA components which can bridge the gap between human motion signals and the complex human behaviours.

This paper is organized as following; Sec. II presents variable space in different levels (LMA and IB), and then based on that, the models, which show the variables dependencies, are presented in Sec. III. Experimental results are shown in Sec. IV, and Sec. V closes the paper with a conclusion and an outlook for future works.

II. Variable Space

In order to parameterize the IBs, we should firstly define some interesting parameters or variables. The proposed model in this work is divided in two abstractive layers. Each of those layers has its own set of variables. These variables are inspired by both Pentland's and Laban's work. The model aims to use body motion information to infer IBs. Thus, we use features obtained by LMA in *Feature Space*, to estimate IB variables, defined by Pentland's definitions in the *Behavior Space*.

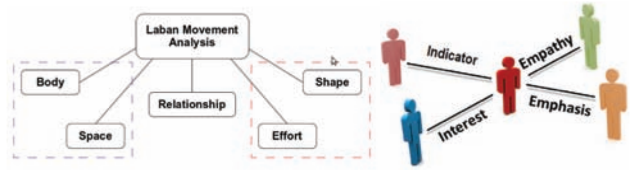


Figure 2. Left) LMA framework with five components [3]. Right) Interpersonal behaviours which were explored in [19]

LMA components	States
Space.Head	Forward, Backward
Space.Hands	Forward, Backward, Up, Down, Right, Left
Effort.Time	Sudden, Sustained
Effort.Space	Direct, Indirect
Shape.Sagittal	Advancing, Retreating
Shape.Vertical	Rising, Sinking
Shape.Horizontal	Spreading, Enclosing

Table I
LMA parameters

A. LMA Components

Composing the *Feature Space* are Laban Components, constitute the observations driving the model. LMA is a framework to describe, interpret and analyze human motions using five different components. Each component deals with different aspect of human motion [21], [11], [3]. All variables defined in feature space are inside the five component set (Fig. 2-Left): *Effort*, *Space*, *Shape*, *Body* and *Relationship*.

Effort describes the dynamics of body motion [21], and is divided in four qualities: *Time*, *Space*, *Weight* and *Flow*. Each of them has a bipolar state. For instance; *Effort.time* presents if the body part's motion is in sustained (like touching carefully movement) or sadden (like punching movement) state, and *Effort.space* describes if the motion is in *direct* (like hand pointing) or *indirect* (like bye bye) state, etc.

Space interprets the trajectory of each body part in a 3D space [21]. Researchers discrete the direction of body motions with some states depend on their applications. *Shape* describes deformation of a body as a blob in three plans; sagittal, vertical and horizontal [23], and it consists some states in each plan; like if the whole body is *rising* or *sinking* in vertical, *advancing* or *retreating* in sagittal, and *spreading* and *enclosing* in horizontal plan. Since we are using hands and head poses in this work, the mentioned blob will consist the space between hands and head. *Body* shows body part relative state to body center [4]. *Relationship* appears as the less studied component and presents the relation between body parts and environmental parameters or others [11].

Depending on the objective, researchers rarely use all LMA components. To quote some examples, [13] uses *Shape* and *Effort* for human action recognition, whilst *Rett* or *Zhao* [21], [29] use *Space* and *Effort* to classify and analyze human gestures. Given the Pentland's descriptions of IB, the selected Laban Components for Feature Space are:

$$Feature\,Space\,\epsilon\,\{Effort, Space, Shape\} \qquad (1)$$

Table.I presents all defined LMA parameters based on the three components for this work.

B. Interpersonal Behaviour

The last decade brought multiple works using LMA-based computational systems to characterize different phenomena in different applications: human-robot interaction [21], human gesture analysis [29], rehabilitation [8] and human movement understanding [13].

All over-mentioned works somehow address human gesture classification in single person perspective. This work goes one step further, using LMA concepts to characterize human behavior rather than gesture, in context of social interaction. To undertake such task, the Pentland's definitions are used to categorize IBs, which are behavior (Honest) signals present in all social interactions. Thus this work defines the set of IB variables as (Fig. 2-Right)); *Indicator*, *Empathy*, *Interest* and *Emphasis*. Each of the IBs variables has two states, which are defined as follows:

$$Indicator\,\epsilon\,\{influenced, influent\} \tag{2}$$

The set.2 presents a variable which consists of two possible states, influenced and influent. As Pentland's describes [19], within a group, there is tendentially someone who tries to have an edge over the remaining. This edge is described as a person's capability to aggregate others around the same line of thought, or more generally, to be the emerge as group leader. Thus we call it as *Indicator* variable.

$$Empathy\,\epsilon\,\{uncoordinated, mimicry\} \tag{3}$$

Mimicry is a state, which is related to *Empathy* behaviour, and as Pentland mentioned in [19], *more empathetic people are more likely to mimic their conversational partners*. Thus the *Empathy* variable has two states (Set.3), *mimicry* state if there is imitation motions, otherwise *uncoordinated* state.

$$Interest\,\epsilon\,\{passive, active\} \tag{4}$$

The *Interest* variable represents whether a person is engaged to the situation or outside context. This behaviour is characterized by, what Pentland describes, as level of activities. Thus we defined two states, *passive* and *active*, for this variable (Set.4).

$$Emphasise\,\epsilon\,\{consistent, inconsistent\} \tag{5}$$

The last defined IB is *Emphasis* variable, which explains a person's focus in a situation, another person or object. If the person has a wandering mind, his/her behavior will be variable or inconsistent. Thus set.5 defines the two possible states of *Emphasis* variable, which are consistent or inconsistent.

C. General Schema of the Variable Spaces

The key point of this work is exploring through all the obtained features in LMA space to estimate the interested classes in IB space. We present that how those features can affect to the estimation of the each IB, and based on those analysis, the sufficient model of the each IB is proposed. Fig. 3 shows an overview of the different variable spaces with all possible connections between those layers. In the next section, the sufficient connection will find out for the each IB.

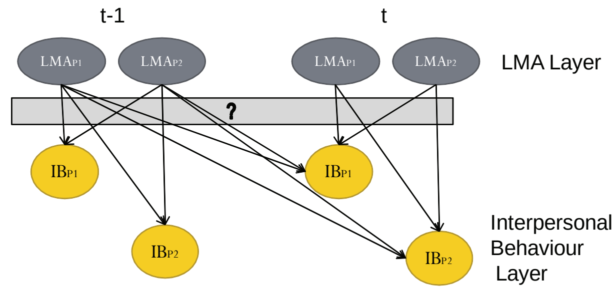


Figure 3. Presenting all possible connection between the two layers in different times. P1 and P2 denote the first and second persons, and LMA_{p1} and IB_{p1} denote all defined variables inside of LMA and IB for the first person.

IBs	IB definition [19]	LMA [11]
Indicator	More energy body motions than others	*Effort*
Empathy	Copying each other activities and nodding	*Space*
Interest	Presenting energetic motion	*Effort*
Emphasis	Movements become jerky or not	*Effort, Space*

Table II

A BRIEF DESCRIPTION OF THE RELATION BETWEEN THE IB DEFINITIONS AND LMA COMPONENTS FOR EACH OF THE IBS

III. GLOBAL HUMAN INTERPERSONAL BEHAVIOUR MODEL

As mentioned before, this work parametrizes IBs with Laban components, by explicitly defining two different abstraction layers. The reason why this work does not infer IB from input signal features directly, is because information will be lost. There are several works that developed models to classify Laban parameters from input signal features [23], [13], [21], [3]. Thus, the present model uses Laban movement analysis as observations. We will describe both IB and LMA components, demonstrating the latter has enough information to characterize human behavior.

As mentioned, four IBs are defined: *Indicator*, *Interest*, *Empathy*, *Emphasis*. In the following sections, the dependencies between LMA and Pentland's definitions are explored (as can be seen in Table.II briefly) and based on them, a Bayesian model for each of IBs is proposed. As can be seen in the following subsections, *Empathy* and *Emphasis* are modeled by dynamic Bayesian approach and explained the reasons for the use of the previous knowledge.

A. Selection of Effective LMA Components in Learning Process

Eq.6 presents a general Bayesian model, and based on that, we explain the general learning process briefly. For all the variables, we only formulate the learning distributions, and the process is analogous for all.

$$P\left(A|B\right) = P\left(A\right).P\left(B|A\right)/P\left(B\right) \tag{6}$$

Variable A is formulated as seen this equation. Observing the second term of the equation, we have the prior distribution $P\left(A\right)$, the likelihood $P\left(B|A\right)$ and the normalization factor $P\left(B\right)$. The likelihood is a conditional probability corresponding to previous knowledge which needs to be learned.

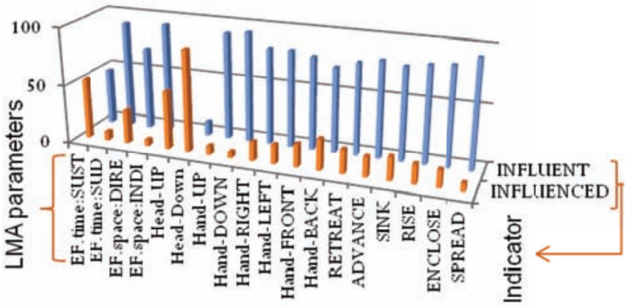


Figure 4. Histogram of the different LMA features for *Indicator* variable

Histogram-like approach is a common supervised learning method. To illustrate this method, let's analyze the learning histogram for the *Indicator* variable (See Fig. 4).

From the collected labeled signals we built an histogram counting all obtained LMA states given the knowledge of the *Indicator* variable state. This allows us to generate the necessary distributions, and this means that, the method allows us to visualize those LMA parameters that better discriminate the IB's states. By comparing the different states of the same LMA variable (e.g. *Effort.Time* for states *Sudden* and *Sustained*), it is possible to empirically select the ones that exhibit the highest dynamics between the IB variable states. In this investigation, depend on the IBs, the previous knowledge of the mentioned person and others also are used, as can be seen in Fig. 3.

B. Indicator Model

In different scenarios, such as people conversation or negotiation, it is interesting to realize who has influence over other participants in many aspects of social context. Thus a person while interacting with others, can be influenced or influent. *Indicator* is the variable which we define with these two possible states.

In [19] most of the influence signals analysis are based on human speech, described in some examples like a student-teacher argument or salary negotiations. However, Krauss mentioned [14] that hand gestures which people produce, play an important role in any communication. We interpret these facts, that when a person is trying to gain influence over others, it usually produces more energy through its body part motion, such as hand motion in a conversation scenario, to be more representative.

LMA framework encompasses a component, *Effort*, which its *analysis is concerned with the changing patterns which occur in the ebb and flow of energy within the body* [11]. Thus to measure the *influent* and *influenced* states of a person, *Effort* component should be sufficient. In this concept, when a person has more representative body part motion, the probability of being influent over others is higher. Thus probability of a person being an *Indicator*, will be the probability of *being influent or not, given* the obtained Effort characteristics, of himself and others. The related histogram which is obtained in the learning process (Fig. 4) also proves the mentioned analysis.

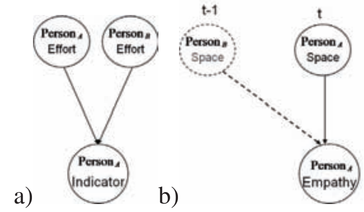


Figure 5. a) The dependencies between LMA parameters and *Indicator* variable ($Person_A$=first person , $Person_B$=second person). b) Dependency diagram among LMA parameters and *Empathy* characteristic for person A. The same can be applied for person B.

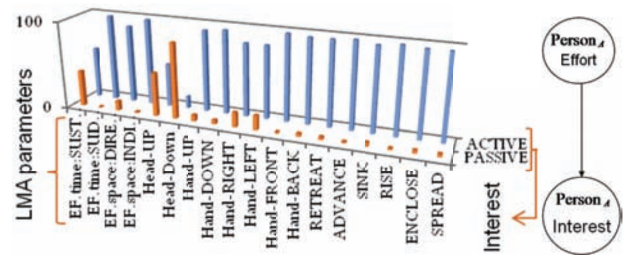


Figure 6. Left) Histogram of the different LMA features in different states of *Interest* variable. Right) Dependency diagram among LMA and *Interest* characteristic.

Based on the dependency diagram in Fig. 5-a, the relation between LMA and *Indicator* is formulated as following:

$$P\left(Ind_i \mid \prod_{h=1:n,i=1:m} Ef_i^h\right) = \frac{P\left(Ind_i\right) \prod_{h=1:n,i=1:m} P\left(Ef_i^h|Ind_i\right)}{\prod_{h=1:n,i=1:m} P\left(Ef_i^h\right)} \tag{7}$$

where Ind_i and Ef_i^h denote respectively, *Indicator* variable for i^{th}person, and *Effort* component variable for h^{th} body part of i^{th} person. n and m denote the number of body parts and persons.

C. Interest Model

In a social interaction, activity level of human body is a visible unconscious signal to present human interest and excitement level. In a communication between people, when a person is interested or excited, presents more energetic motion. A visible example to show the issue presented in [19] is connection between activity level and excitement for children in special events like a birthday party. Excited kids usually talk faster and louder, fidget more and run around, and similar of those effects also happen for adults. Thus this IB also relates how much energy is consumed by the person which can be interpreted by *Effort* component of LMA.

As seen in Fig. 6-left, most of the features are quite dynamic, but those features which include less parameters and also also cover the mentioned analysis are selected.

The difference between *Interest* and *Indicator* variables is that for *Interest* just one person's data is sufficient but for *Indicator*, we need to have more than one person involved (in social context).

Based on the dependency diagram shows in Fig.6-right, the relation between LMA and *Interest* behaviour is formulated as following:

Algorithm 1 Algorithm to decide the similarity value for each LMA parameter, to be used for *mimicry* histogram generation (see Fig. 5-b).

for each $f_A \in LMA\,(A_t)$
f_B: corresponding feature to f_A
if value(f_A^t) = value(f_B^{t-1})
$f_A^t.mimicry \leftarrow' same'$
else
$f_A^t.mimicry \leftarrow' different'$
end.

$$P\left(Int_i \,|\, \prod_{h=1:n} Ef_i^h\right) = \frac{P\,(Int_i)\,\prod\limits_{h=1:n} P\left(Ef_i^h|Int_i\right)}{\prod\limits_{h=1:n} P\left(Ef_i^h\right)} \qquad (8)$$

where Int_i and Ef_i^h denote *Interest* variable for i^{th}person and *Effort* component variable for h^{th} body part of i^{th} person respectively.

D. Empathy Model

When people who are deeply engaged in a conversation are on the same wavelength, it is called *Empathy* [19]. *Empathy* can be felt by some interactive motion signals. One of the common of those signals is mimicry. The engaged people copy each other activities, such as smiling, body gesture, head nodding and etc. during a conversation. Those mimicry motions, usually occur when motion is similar in space, but not necessarily *relating to its dynamics*. Thus the LMA spatial-based features are more meaningful and reliable inputs to discretize this IB. *Space* component of LMA describes body motion trajectory, *specific direction, level, distance, or degree of motion* [11].

To prove the idea, Fig. 7-left) and Fig. 7-right) show generated histograms that will be used for *mimicry* and *uncoordinated* states, respectively. In each of these two histograms, the first dimension shows the LMA parameters, and the second dimension indicates the decided value for mimicry or uncoordinated states. For each person (for example A) these values are obtained by considering the difference between the corresponding LMA features among the current person in time t (f_A^t) and the other person in previous time (f_B^{t-1}). Such a process is shown in Algorithm.1 for the *mimicry* state, and is similar for *uncoordinated* state.

Comparing the two histograms, it can be seen that *Space* component has highly distinct behaviors than the remaining. Thus in Eq.9, just space component features of the person and previous data of other person are used.

Fig. 5-b presents the relation between LMA and *Empathy*, which is formulated as following:

$$P\left(Emp_i(t) \,|\, \prod_{h=1:n}\left(Sp_i^h(t)\prod_{j=1:m,j\neq i} Sp_j^h(t-1)\right)\right) =$$
$$\frac{P(Emp_i(t))\prod\limits_{h=1:n,j=1:m,j\neq i} P\left(Sp_i^h(t)\,Sp_j^h(t-1)|Emp_i(t)\right)}{\prod\limits_{h=1:n} P\left(Sp_i^h(t)\prod\limits_{j=1:m,j\neq i} Sp_j^h(t-1)\right)} \qquad (9)$$

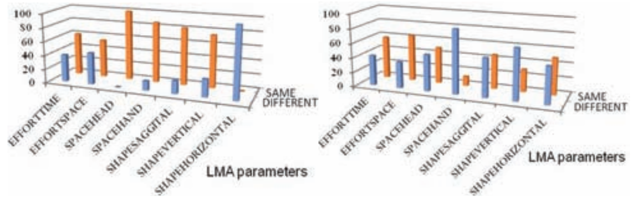


Figure 7. Histograms of LMA variable states similarity of two persons between time t and $t-1$ for the both *Empathy* variable states; Mimicry histogram is represented in the left and Uncoordinated in the right image. The blue and orange bars show statistically how much each of LMA parameters data belong to person A at time t and person B at time t-1, are different and the same, respectively.

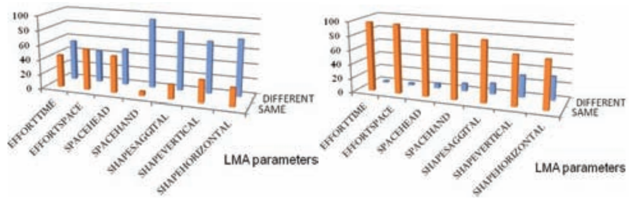


Figure 8. Histogram of LMA variable states similarity of one persons between time t and $t-1$ for the both *Emphasis* variable states; *Consistent* histogram is represent in the left and *Inconsistent* in the right image. The blue and orange bars show statistically how much each of LMA parameters data belong to person A at time t and t-1, are different and the same, respectively.

where $Emp_i(t)$ and $Sp_i^h(t)$ denote *Empathy* variable for i^{th}person and *Space* component variable for h^{th} body part of i^{th} person at time t, respectively. n and m denote the number of body part and person. In the experiment, we just applied a couple of persons and three body parts data, however it can be extended to more persons and body parts data.

E. Emphasis Model

When a person is thinking about different things simultaneously, his/her speech and movements become jerky and inconsistency paced ([25] in [19]). It means that depends on context, people's emphasis can be consistent or variable, and the relative consistency or variability of human activity conveys different messages for people. Those messages can play an important role in social aspect. To estimate this IB we should look for variation of both *Space* and *Effort* components features of the person along time. When they remain constant, it means the person is focused or its behavior is consistent, giving emphasis to that person's actions.

Similar of previous section, Histograms of the *Emphasis* model are generated and presented in Fig. 8, but instead of using previous data of other person in *Empathy* model, previous data of the same person is used in the current model. The left image corresponds to the *Consistent* state, and is presenting whether LMA parameters for the person at time t, correspond to the LMA parameters of the same person at time $t-1$ or not. The right image presents the same histogram but for *Inconsistent* state. Comparing the two histograms, it can be seen that *Space* and *Effort* components have high distinct behaviors. The following equation are expresses the Bayesian model (see Fig. 9-a) for *Emphasis* variable:

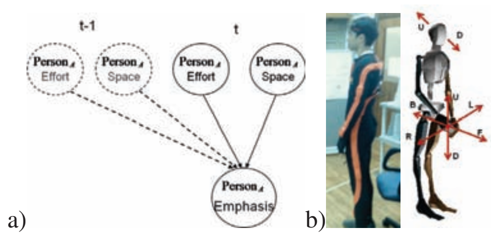


Figure 9. a) Dependency diagram among LMA parameters and *Emphasis* characteristic. b) A person with a special suit (motion tracker) for 3D data capturing and *Space* parameters presented on a dummy.

$$P\left(Emf_{i(t)} \mid \prod_{h=1:n}\left(Sp^h_{i(t)}\, Ef^h_{i(t)}\, Sp^h_{i(t-1)}\, Ef^h_{i(t-1)}\right)\right) = \frac{P\big(Emf_{i(t)}\big)\prod_{h=1:n}\Big(P\big(Sp^h_{i(t)}\, Sp^h_{i(t-1)}\, Ef^h_{i(t)}\, Ef^h_{i(t-1)} \mid Emf_{i(t)}\big)\Big)}{\prod_{h=1:n}\Big(P\big(Ef^h_{i(t)}\big)\, P\big(Ef^h_{i(t-1)}\big)\, P\big(Sp^h_{i(t)}\big)\, P\big(Sp^h_{i(t-1)}\big)\Big)} \tag{10}$$

where $Emf_{i(t)}$ and $Ef^h_{i(t)}$ and $Sp^h_{i(t)}$ denote *Emphasis* variable for i^{th}person and *Effort* and *Space* component variables for h^{th} body part of i^{th} person at time t.

IV. Experiments

A set of experiments have been carried out to demonstrate the effectiveness of the proposed models. The experiments are performed in the smart-room of the MRL of ISR[1]. Our setup is comprised of a 3D human motion tracking sensor, called MovenSuit[2] (see Fig. -b), and a network of cameras installed on the ceiling of the room. A set of conversation scenarios are defined in which the contexts are the IB activities performed by two persons. Note that the proposed model has capability of being used for a multi persons case however here due to some limitation in the data acquisition setup we have just used two persons in order to prove the concept. In each scenario the body movements for each person are recorded by using the MovenSuit device. After recording the scenarios in each sequence and for each of the acting person an expert, called annotator, manually annotated the LMA parameters and IB states by observing the recorded videos from the ceiling cameras. The used LMA parameters and IB states are based on our definitions provided on sections 2.1 and 2.2. Each sequence has a length about 400 seconds.

The annotated data by the expert is used for learning stage. For classifications, the LMA parameters are automatically extracted from the 3D tracker based on our previous works [13]. The frequency for both annotation and classification stages is 1Hz. Among the annotated data, half of them is used for learning and the other half is used for classification.

For the purpose of classification, the automatically obtained LMA parameters from each frame are fed to the proposed IB models. Fig. 10 shows an exemplary short sequence including five frames (5 sec. length, labeled from 1 to 5). The extracted LMA features related to these sequence are fed to each IB model. The histogram in this figure represents the output for each IB for the seconds 2 to 5.

[1]http://paloma.isr.uc.pt/mrl/
[2]http://www.xsens.com/en/general/mvn

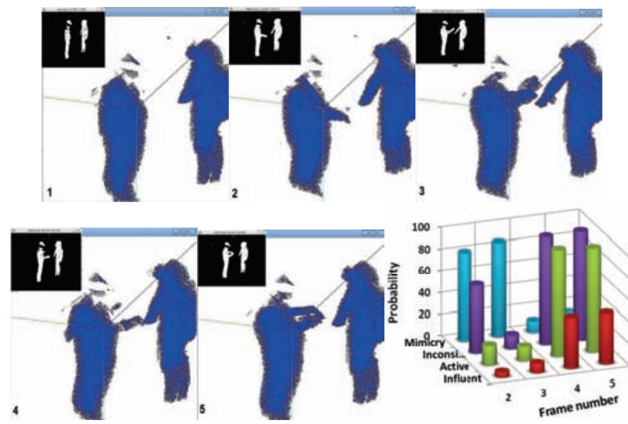


Figure 10. an exemplary short sequence including five frames (5 sec. length, labeled from 1 to 5). The extracted LMA features related to these sequence are fed to each IB model. The histogram in this figure represents the output for each IB for the seconds 2 to 5.

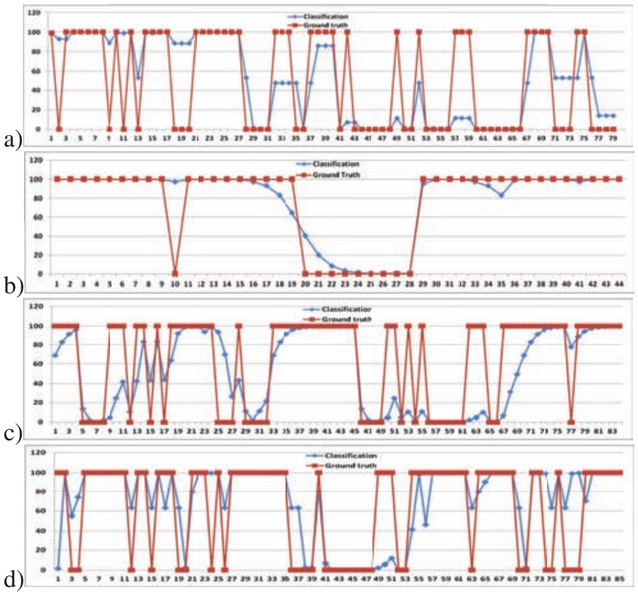
	Indicator		Interest		Empathy		Emphasis	
	Inft	Infd	Act.	Pas.	Mim.	Unc.	Con.	Inc.
PCR	72%	70%	93%	90%	80%	74%	88%	53%

Table III
Positive Classification Rate (PCR) results for IBs models

In Fig. 11 presents the classification results for some long sequence data. In Fig. 11-a) the result for the *Indicator* model is plotted. As can be seen, the classification result converges after passing a maximum of three frames. The convergence for the *Interest* model, shown in Fig. 11-b), is faster. The reason is because as can be seen in Fig. 4-right, this model just depends to the data of the same person independent of previous data.

Fig. 11-c) presents the *Empathy* model results. The graph is divided in two parts. The first part, corresponds to the first 33 frames and presents the results based on using head-space feature (nodding), and the rest are based on comparison algorithm proposed in Alg. 1. As can be seen, the first part shows faster convergence but we have slower convergence for the second part. The reason is that the nodding model requires no data from previous time whereas the comparison algorithm needs data from previous moments, which makes the convergence slower.

Fig. 11-d) presents the *result for Emphasis* model. As seen, at the most of parts the classification result converges to the ground truth. Only a few frames diverges from the ground truth signal ($78^{th}, 79^{th}$ frame), because the states were changed fast. Table.III summarizes the positive classification results for all IB variables based on the obtained LMA states at every second. In this table, the classifications percentage for the *Emphasis* state is lower than the other IBs. It is due to the difficulty of interpretation for this behaviour state even for an expert. As can be seen in the presented results, when the observation data changes, it takes a while to converge. We expect to have better results with faster convergence if a higher frequency could be used (currently 1Hz) [12].



a)
b)
c)
d)

Figure 11. Classification results over the time axis for the four IBs states *Influent*, *Active*, *Mimicry*, *Inconsistent* which are respectively shown in (a), (b), (c) and (d).

V. Conclusion and future works

In this paper, a new approach to parameterize human Interpersonal Behavior (IB) using body motion description (LMA) evidence was proposed. To find the dependencies between body part motions-based features and the IBs, we inspired ourselves in the definitions of social signal by Alex Pentland and the human motion descriptor of Rudolph Laban. We used Bayesian Network (BN) to define our models and an histogram approach to perform supervised learning. The results are encouraging, and motivate us to further explore this work.

For further improve of this work we intent to use *Relationship* component of LMA to model interaction of people with the environment. The model will be scaled to estimate social roles as described in Pentland's work. We will develop a system that could allow the model to improve its update rate. In this work, the input data are obtained by using motion tracker which is less noisy but more appropriate for prove of the concept. However we believe that the proposed models can be adapted with any types of input data. Therefore in our future work we will use the input data from a marker-less human-body 3D reconstraction technique [2].

VI. Acknowledgment

This work was financially supported by a PhD grant (SFRH/BD/70640/2010) from the Portuguese Foundation for Science and Technology (FCT).

References

[1] J.K. Aggarwal, Q. Cai, W. Liao, and B. Sabata. Articulated and elastic non-rigid motion: a review. In *In Proc. IEEE Workshop on Motion of Non-Rigid and Articulated Objects*, pages 2–14, 1994. Proceedings of the IEEE Workshop on Motion of Non-Rigid and Articulated Objects.

[2] Hadi Aliakbarpour and Jorge Dias. 3d reconstruction based on multiple virtual planes by using fusion-based camera network. *Journal of Computer Vision (IET)*, 2012.

[3] N.I. Badler, C.B. Phillips, and B.L. Webber. *Simulating Humans: Computer Graphics,Animation, and Control*. Oxford Univ. Press, 1993.

[4] D. Bartenieff, I. & Lewis. *Body Movement: Coping with the Environment*. Gordon and Breach Science, New York, 1980.

[5] A.F. Bobick. Movement, activity and action: the role of knowledge in the perception of motion. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 352(1358):1257–1265, 1997.

[6] C. Cedras and M. Shah. Motion-based recognition: a survey. *Image Vision Comput*, 13:129–155, 1995.

[7] Wen Dong, Bruno Lepri, Alessandro Cappelletti, Alex Sandy Pentland, Fabio Pianesi, and Massimo Zancanaro. Using the influence model to recognize functional roles in meetings. In *Proceedings of the 9th ICMI*, pages 271–278, New York, USA, 2007.

[8] A. Foroud and I.Q. Whishaw. Changes in the kinematic structure and non-kinematic features of movements during skilled reaching after stroke: A laban movement analysis in two case studies. *Journal of Neuroscience Methods*, 158:137–149, 2006.

[9] Donelson R. Forsyth. *Group Dynamics*. Wadsworth/Cengage, Belmont, CA, 2010.

[10] D. M. Gavrila. The visual analysis of human movement: A survey. *Computer Vision and Image Understanding*, 73:82–98, 1999.

[11] Ann Hutchinson. *Labanotation*. Oxford Univ. Press, 1974.

[12] Kamrad Khoshhal, Hadi Aliakbarpour, Joao Quintas, Paulo Drews, and Jorge Dias. Probabilistic lma-based classification of human behaviour understanding using power spectrum technique. In *13th International Conference on Information Fusion*, Edinburgh, UK, July 2010.

[13] Kamrad Khoshhal, Hadi Aliakbarpour, Joao Quintas, Martin Hofmann, and Jorge Dias. Probabilistic lma-based human motion analysis by conjugating frequency and spatial based features. In *WIAMIS*, 2011.

[14] Robert M. Krauss and Uri Hadar. *Gesture, speech, and sign*, chapter The role of speech-related arm/hand gestures in word retrieval, pages 93–116. Oxford University Press, 1999.

[15] Lian Loke, Astrid T. Larssen, Toni Robertson, and Jenny Edwards. Understanding movement for interaction design: frameworks and approaches. *Personal Ubiquitous Comput.*, 11:691–701, December 2007.

[16] Thomas B. Moeslund, Adrian Hilton b, and Volker KruÂšger. A survey of advances in vision-based human motion capture and analysis. *Computer Vision and Image Understanding*, pages 90–126, 2006.

[17] Maja Pantic, Alex Pentland, Anton Nijholt, and Thomas Huang. Human computing and machine understanding of human behavior: a survey. In *Proceedings of the 8th ICMI*, pages 239–248, USA, 2006.

[18] Alex Pentland. Looking at people: Sensing for ubiquitous and wearable computing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22:107–119, 2000.

[19] Alex (Sandy) Pentland. *Honest Signals: How They Shape Our World*. The MIT Press, 2008.

[20] Ronald Poppe. Vision-based human motion analysis: An overview. *Computer Vision and Image Understanding*, 108:4–18, 2007.

[21] Joerg Rett. *ROBOT-HUMAN Interface using LABAN Movement Analysis Inside a Bayesian framework*. PhD thesis, University of Coimbra, 2008.

[22] M. S. Ryoo and J. K. Aggarwal. Recognition of composite human activities through context-free grammar based representation. In *Proceedings of the CVPR '06*, pages 1709–1718, USA, 2006.

[23] Luis Santos and Jorge Dias. Human motion classifier based on laban movement analysis. In *COGSYS*, ETH Zurich, 2010.

[24] Xiaofan Sun, Anton Nijholt, Khiet P. Truong, and Maja Pantic. Automatic visual mimicry expression analysis in interpersonal interaction. In *CVPRW*, pages 40–46, USA, 2011.

[25] Willem B. Verwey and Hans A. Veltman. Detecting short periods of elevated workload. a comparison of nine workload assessment techniques. *Journal of Experimental Psychology. Applied*, 2(3):270–285, 1996.

[26] A. Vinciarelli, H. Salamin, and M. Pantic. Social signal processing: Understanding social interactions through nonverbal behavior analysis. In *CVPR Workshops*, pages 42 –49, 2009.

[27] Alessandro Vinciarelli, Maja Pantic, and Hervé Bourlard. Social signal processing: Survey of an emerging domain. *Image Vision Comput.*, 27(12):1743–1759, 2009.

[28] Liang Wang, Weiming Hu, and Tieniu Tan. Recent developments in human motion analysis. *Pattern Recognition Society*, pages 585–601, 2003.

[29] L. Zhao and N.I. Badler. Acquiring and validating motion qualities from live limb gestures. *Graphical Models*, pages 1–16, 2005.