Interrelation Analysis for Interpersonal Behaviour Understanding in Social Context

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Abstract: In this paper we study a probabilistic approach to characterize Interpersonal Behaviours (IBs) in a social concept by exploring the existent interrelation between body motion features. Human activities were explored in different level of complexities, such as social-based human activity. To bridge the existent big gap between human body motions and the IBs analysis, a set of proper dependencies definition between the features is vital. Inspired in the works of Alex Pentland and Rudolph Laban, we proposed a couple of layers of analysis. In the first layer, we analyse human body parts motions based on a known body motion descriptor, Laban Movement analysis (LMA). LMA composes a set of components which provides different types of human movement features. We investigated the interrelation between those LMA features of a couple of persons to provide a proper model to estimate the IBs in the second layer. To reach the goal, LMA components are used as body motion features. To computerize the model, Dynamic Bayesian Network (DBN) approach is used, because of its flexibility in development and implementation of the dependencies and interrelations. The results show the importance of the interrelations to have more accurate results of the IBs estimations.

Keywords: Interrelation analysis, interpersonal behaviour analysis, social signals, Bayesian approach, Laban movement analysis.

1. INTRODUCTION

People use their skill of body motions in communication to express better their points. In any human interaction, between human body motions, there are several meaningful relations with respect to each others. Imagine two persons interact to each other, and each of them tries to respond other's request. During those interactions we could see a relation between their body motions which assist us to realize the people and context situation even when we could not hear their conversation. Those features also are more reliable features to understand actual human behaviours, which Pentland call it "*Honest signals*" (Pentland [2008]).

In a social concept, it can be realized that each person is interested or influenced to communicate with others by observing their body motions. For instance in a TV show program, the showman use body motions too much to attract audiences, but a newscaster is in opposite situation. However it also depends on the person's attitude, culture, etc.

In this paper, we intend to explore in the existent relations between people body parts motions, which plays an important role, to analyse the Interpersonal Behaviours (IBs). To implement the idea we propose Laban Movement analysis (LMA), which is a known body motion descriptor as a mid-level features. LMA has several components, which were investigated, analysed and modeled (Zhao and Badler [2005], Rett [2008], Khoshhal and et al. [2011b]), to describe human movements with several symbols. Those descriptions are useful not only on the modeling of complex human activities, but also for finding out and analysing the existent relationships between body parts motions in different IBs. Dynamic Bayesian Network (DBN) is the proper approach to have the flexibility to perform those dependencies (relations).

In the last decade, researchers were interested to understand human behaviours in different applications, such as surveillance, security and social systems, thus many approaches were introduced. Maja Pantic's group categorized those approaches based on the existent types of observation data; facial expression, voice, and body motion (Pantic et al. [2006]). Each of those approaches has own advantages and disadvantages. In this paper, we attempt to rely just on body motion types features to analyse human behaviours in social aspect.

In many applications, having an acceptable visibility of face image and voice data is complicated. For instance in many public places which usually there are several cameras around, collecting body motion type features are more proper than face and voice ones. Most of the attempts in this kind of applications just used motion-based features from the human as a blob, which cannot be useful for analysing of complex types of human activities such as handshaking or even more complex such as mimicry. Body parts motions are very informative for analysing human activities which are not applicable even by other types of features. By progressing of existent techniques about 3D reconstruction of human body, such as (Aliakbarpour and

Reference	Description
Aggarwal and et al. [1994]	Covered various methods used in articulated and elastic non-rigid motion.
Cedras and Shah [1995]	Methods of motion extraction, recognition of body parts and body configuration estimation.
Gavrila [1999]	The existent works in human motion analysis in terms of 2D and 3D approaches.
Pentland [2000]	Touched on several interesting topics in human motion analysis and its applications.
Wang et al. [2003]	Vision-based human motion analysis (detection, tracking and activity understanding).
Moeslund et al. [2006]	Vision-based human motion capture (initialization, tracking, pose estimation and recognition).
Poppe [2010]	Modeling and estimation phases of human motion and human action classifiers.

Table 1. List of surveys around body motions-based investigations.

Dias [2010]), this type of features can play an important role to analyse complex human behaviours such as human-human interaction or IBs. Several surveys were published around that in different taxonomies and objectives, and some of them are summarized in Table.1.

As can be seen in previous works, analysing IB based on human body motion is less explored, however there are some attempts such as (Park and Trivedi [2008]) that used whole body as a blob which is very restricted to analyse complex human activities. Ryoo and Aggarwal works (Ryoo and Aggarwal [2009]) were more progressed in this field. They defined an descriptor for human motion and tried to branch whole body in three parts; head, upper body and lower body, through 2D side view data. But using a limited body motion descriptor, upper and lower body instead of body parts, and 2D data, make several restrictions which we attempt to avoid them.

Pentland's group was the first one, who attempted to computerize the IBs in social aspect (Pentland [2008]). However this filed of study is new, but Vinciarelli et al. in (Vinciarelli et al. [2009]) provided a short survey around that. In the social aspect, one of the important communication signals is body part motions. Pentland's group has many works about social signal processing in different channels of communication. In this paper we intend to explore more in the existent relations between body parts motion of people for reaching to the social signals based on the Pentland definitions. Thus, contributions of this work are;

1- Using just body motions data to analyse IBs, since others (Dong et al. [2007]) rely not only on the body motions-based features, but also on the speech-based ones. This property allows us to use this approach more in general applications with less restrictions.

2- Using LMA components as body motion type features instead of using Low Level Features (LLFs) directly, to understand IBs. Those components are very close to LLFs, and collected the most informative features of body motions, that allows the experts such as choreographers to describe and interpret any complex human body movements. Thus, as can be seen in the previous works (Khoshhal and et al. [2011b], Rett [2008], Zhao and Badler [2005]), those LMA-based features can be obtained precisely without losing the generalizability of the system.

3- Interrelation between body parts motions of people during different IBs are investigated. This can be applicable and useful only while we use a standard body motion descriptions, otherwise exploring in LLFs is complicated.

4- Implementing the useful dependencies by DBN, and obtaining more than 77% accuracy.

Section.2 presents variable space in different levels (LMA and IB), and then based on that, the interrelations analysis for each of IBs, which shows the variables dependencies, are presented in Section.3. Experimental results and the related discussions are described in Section.4, and Section.5 closes with a conclusion and future works.

2. VARIABLE SPACE

To analyse human interaction with another person, we need to concern about the interrelation between the couple of person movements. For instance; handshaking action is as an agreement's sign of body motions between two persons. Almost all people do the same movements with the same interrelations, that everyone can easily realize the handshaking action. Every person, depend on the context, has own style of movement for a specific action, and more details can be obtained (e.g. if it is a condolence handshaking or sanitary handshaking), however all of them follow the same role for moving of their body parts related to another person's movement. Thus depend on the goal we need to find the proper features and the interrelation between them.

To explore in the relations between features, first we need to define the features properly. Thus the features are presented in different variables which each has some states, as can be seen in the following sub-sections.

2.1 LMA Components

Laban Movement Analysis (LMA) is a known body motion descriptor and interpreter by using five components which they deal with different human motion properties (Rett [2008], Zhao and Badler [2005], Hutchinson [1974], Badler et al. [1993]). All variables which defined as Feature Space are inside the five component sets: *Effort*, *Space*, *Shape*, *Body*, *Relationship*.

Effort deals with the dynamics of body motion (Rett [2008]), and consists of four sub-components (*Time*, *Space*, *Weight* and *Flow*) with bipolar state for the each of them. *Space* is concerned with the trajectory of each body part (Rett [2008]), *Shape* interpret the deformation of a body as a blob in the three plans; sagittal, vertical and horizontal (Khoshhal and et al. [2011b]), and *Body* describe body parts situation related to body center (Bartenieff [1980]). *Relationship* appears as the less studied component and presents the relation between body and environment (Hutchinson [1974]).

LMA Comp.	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 2. LMA parameters

Depending on the objective, researchers rarely use all LMA components. To quote some examples, (Khoshhal and et al. [2011b]) uses *Shape* and *Effort* for human action recognition, whilst Rett (Rett [2008]) and Zhao (Zhao and Badler [2005]) use *Space* and *Effort* to classify and analyse human gestures. Given the Pentland's descriptions of IB, the Feature Space will contain *Effort*, *Space* and *Shape* components. Table.2 presents all defined LMA parameters based on the three components for this work. Table.2 presents all defined LMA parameters based on the three components for this work.

2.2 Interpersonal Behaviour

The term 'interpersonal' focuses on the connections between two persons, and the behaviour between these two individuals will depend on the context of their relationship. For example, the way that between two colleagues behave to each other will be different to the communication between a teacher and a student. In this work, we attempt to explore in the interrelation between two individuals body motions to estimate IBs.

The last decade brought multiple works of computational systems using LMA parameters to characterize different phenomena in different applications: human-robot interaction (Rett [2008]), human gesture analysis (Zhao and Badler [2005]), rehabilitation (Foroud and Whishaw [2006]), surveillance systems (Khoshhal and et al. [2011a]) and human movement understanding (Khoshhal and et al. [2011b]).

All those mentioned works were individual-based analysis, but in this paper we are attempted to goes one step further, using LMA concepts to characterize IBs rather than gesture, in social interaction-based context. To undertake such task, the Pentland's definitions are used to categorize IBs, which are behaviour (Honest) signals present in all social interactions. Thus the set of IB variables defined as: *Indicator*, *Empathy*, *Interest*, *Emphasis*. Each of the IBs variables have two states, which are defined as follows:

$$\begin{gathered} Indicator \in \{influenced, influent\} \\ Empathy \in \{uncoordinated, mimicry\} \\ Interest \in \{passive, active\} \\ Emphasise \in \{consistent, inconsistent\} \end{gathered} \tag{1}$$

In any group conversation and interaction, there is tendentially someone who tries to have an edge over the remaining. This edge is a person's skill to bring others together around the same line of thought, and come out as a group leader. Thus we call it as *Indicator* variable. Set.1 presents the variable which consists of two possible states, influenced and influent. Mimicry is a state, which is related to *Empathy* behaviour, and as Pentland mentioned in (Pentland [2008]), *more empathetic people are more likely to mimic their conversational partners.* Thus the *Empathy* variable has two states (Set.1); *mimicry*, if there is imitation motions, otherwise *uncoordinated* state.

The *Interest* variable represents whether a person is involved to the situation or outside context. This IB is characterized by, what Pentland describes has, level of activities. When a person are interested to the situation, shows more activities like speaking and body motions. Thus we defined two states, *passive* and *active*, for this variable (Set.1). *Emphasis* variable is the last IB, and explains a person's focus in a situation. If the person has a wandering mind, its behavior will be variable or inconsistent. Thus Eq.1 defines the two possible states of *Emphasis* variable, which are *consistent* or *inconsistent*.

3. INTERRELATION ANALYSIS IN A BAYESIAN FRAMEWORK

This work explore in the existent relations between people's body motions through the Laban components concepts, to parametrizes IBs. The reason why this work does not infer IB from input signal features directly, is because information will be lost, because of existent big gap between them. There are several works that developed models to classify Laban parameters from input signal features (Khoshhal and et al. [2011b], Rett [2008], Badler et al. [1993], Zhao and Badler [2005]). Thus, the present model uses Laban movement analysis as observations. We will find out the interrelation between LMA components, for each IBs. As mentioned, four IBs were defined: *Indicator*, *Interest*, *Empathy*,*Emphasis*. The dependencies between LMA's parameters for each IBs are studied as following.

3.1 Inference: Learning

Inference and learning are key issues in Bayesian modeling. Eq.2 presents a general Bayesian model equation, and based on that we explain the general learning process. For the all variables, we only formulate the learning distributions, as the process is analogous for all.

$$P(A|B) = \frac{P(A).P(B|A)}{P(B)} \tag{2}$$

Variable A is formulated as in Eq.2. Observing the second term of the equation, we have the prior distribution $P(A)$, the likelihood $P(B|A)$ and the normalization factor $P(B)$. The likelihood is a conditional probability corresponding to previous knowledge which needs to be learned. Hence we present a histogram-like approach to perform a supervised learning. To illustrate this method, let's analyse the learning histogram for *Indicator* variable in Fig. 1.

From an annotated signal we built an histogram by counting all observed LMA states given the knowledge of the *Indicator* variable state. This process allows us to generate the necessary distributions. The method also allows to visualize the LMA parameters that better discriminate the IB's states such as *Indicator* variable states. By comparing the different states of the same LMA variable (e.g. Effort Time for the *Sudden* and *Sustained* states), it is possible to select the ones that exhibit different behaviours for each IB variable state. In this investigation, depend on the IBs,

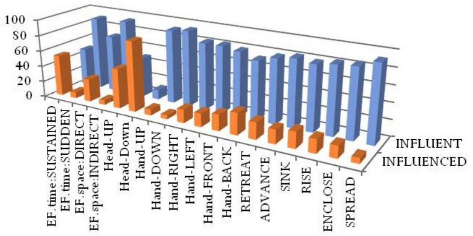

Fig. 1. Histogram of learning process for *Indicator* variable.

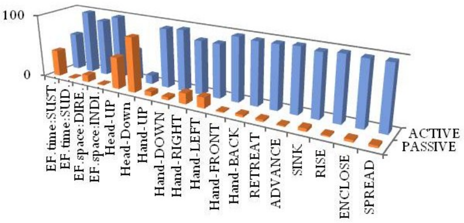

Fig. 2. Histogram of learning process for *Interest* variable.

the previous knowledge of the mentioned person and the other one also is explored.

- *Indicator*

As seen in the histogram (Fig. 1), *Effort* parameters are sufficient features which can distinguish *Indicator* states. However *Shape* parameters also seems to be potentially good features, but we can not find a sensible relation between different states of the each variables. In this IB, there is somehow a competition between people to affect other, thus this IB model should concern about other *Effort* parameters also. This fact re-enforces the dependencies established using Pentland and Laban definitions. Thus based on this analysis, the *Indicator* model is defined such as Eq.3.

$$P\left(Ind_i \mid \prod_{h=1:n,j=1:m} Ef_j^h\right) = \frac{P\left(Ind_i\right) \prod_{h=1:n,j=1:m} P\left(Ef_j^h \mid Ind_i\right)}{\prod_{h=1:n,j=1:m} P\left(Ef_j^h\right)} \quad (3)$$

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 part and person.

- *Interest*

This IB is the simplest one that don't need others observations data and previous knowledge also. As can be seen in Fig. 2, most of the features are quite sufficient, thus the features that includes less parameters was selected. Thus, the *Effort* parameters are selected (Eq.4).

$$P\left(Int_i \mid \prod_{h=1:n} Ef_i^h\right) = \frac{P\left(Int_i\right) \prod_{h=1:n} P\left(Ef_i^h \mid Int_i\right)}{\prod_{h=1:n} P\left(Ef_i^h\right)} \quad (4)$$

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.

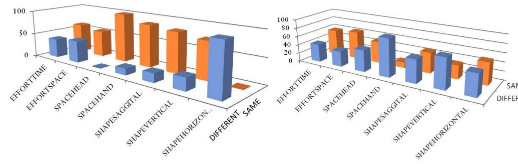

Fig. 3. Histogram of LMA variable states similarity of two persons between time t and $t-1$ for the both *Empathy* variable states; Mimicry histogram is represent in left and Uncoordinated in the right image.

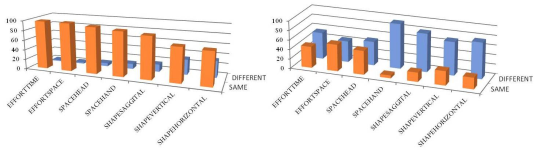

Fig. 4. Histogram of LMA variable states similarity of one persons between time t and $t-1$ for the both *Emphasis* variable states; *Consistent* histogram is represent in left and *Inconsistent* in the right image.

- *Empathy*

Fig. 3 presents two histograms for the *Empathy* model, which use variable knowledge at previous time $t-1$. The left image corresponds to the Mimicry state, and is presenting whether LMA parameters for the first person at time t, correspond to the same LMA parameters of the other person at time $t-1$ or not. The right image presents the same results but for Uncoordinated state. Comparing the two histograms, the *Space* component has highly distinct behaviors than the remaining. Thus in Eq.5, just space component features of the person and previous data of other person are used.

$$P\left(Emp_i(t) \mid \prod_{h=1:n}\left(Sp_i^h(t) \prod_{j=1:m,j\neq i} Sp_j^h(t-1)\right)\right) = \frac{P\left(Emp_i(t)\right) \prod_{h=1:n,j=1:m,j\neq i} P\left(Sp_i^h(t)\, Sp_j^h(t-1) \mid Emp_i(t)\right)}{\prod_{h=1:n} P\left(Sp_i^h(t) \prod_{j=1:n,j\neq i} Sp_j^h(t-1)\right)} \quad (5)$$

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.

- *Emphasis*

Histograms of the *Emphasis* model were presented in Fig. 4. The left image corresponds to the *Consistent* state, and it is presenting whether LMA parameters for a person at time t, correspond to the same LMA parameters of the person at time $t-1$ is similar or not. The right image presents the same histogram but for *Inconsistent* state. Comparing the two histograms, the *Space* and *Effort components* have high distinct behaviors. Thus in Eq.6, both *Space* and *Effort* component features of a person and it's previous data are used.

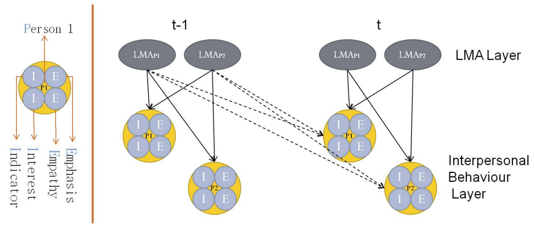

Fig. 5. A global model for IBs analysis, and presenting the dependencies

$$
P\left(Emf_{i(t)} \mid \prod_{h=1:n}\left(Sp^h_{i(t)}\, Ef^h_{i(t)}\, Sp^h_{i(t-1)}\, Ef^h_{i(t-1)}\right)\right) = \frac{P\left(Emf_{i(t)}\right)\prod_{h=1:n}\left(P\left(Sp^h_{i(t)}\, Sp^h_{i(t-1)}\, Ef^h_{i(t)}\, Ef^h_{i(t-1)} \mid Emf_{i(t)}\right)\right)}{\prod_{h=1:n}\left(P\left(Ef^h_{i(t)}\right)P\left(Ef^h_{i(t-1)}\right)P\left(Sp^h_{i(t)}\right)P\left(Sp^h_{i(t-1)}\right)\right)} \quad (6)
$$

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.

The learning distributions are formulated based on the likelihood terms of the each IBs variable models. Eq.7 presents all the Bayesian formulas which should be estimated in learning process. Fig. 5 presents the whole model of IBs based on those analysis.

$$
\begin{array}{c}
Indicator : \forall h, i,\ P\left(Ef^h_i \mid Ind_j\right) \\
Interest : \forall h, i\ P\left(Ef^h_i \mid Int_i\right) \\
Empa : \forall h, i, j, i \neq j\ P\left(Sp^h_i(t)\, Sp^h_j(t-1) \mid Emp_i(t)\right) \\
Emph : \forall h, i\ P\left(Sp^h_{i(t)} Sp^h_{i(t-1)} Ef^h_{i(t)} Ef^h_{i(t-1)} \mid Emf_{i(t)}\right)
\end{array} \quad (7)
$$

4. EXPERIMENTS

In this work, we intend to analyse the relations between human body motions of a couple of persons to understand IBs, however sometimes, it is difficult to realize those IBs just based on body motions. Imagine if we just can see people body motions from a distance, still the IBs are understandable, if there are some relevant body motions during their activities. In the experimental part, a couple of video sequences of data of a couple of persons body motions were collected. In those sequences, a couple of persons tried to influence each other, without any constraints. The input data for our models, was obtained by annotating the video data with LMA and IB states at every second. The LMA parameters and IB states used in the annotation are listed on subsections 2.1 and 2.2.

The learned distributions for our models are then used to classify IB according to the observed LMA states. The results are the probabilities of each state of the IB variables at a frequency of 1Hz.

4.1 Discussions

The relations between Pentland's definitions and LMA components are approved by the analysis the interrelations for each IBs in sections 3. Based on those dependencies, a Bayesian model for each of IBs is proposed. On the subsections, *Empathy* and *Emphasis* are modeled by dynamic Bayesian approach and explained the reasons for the use of the previous knowledge.

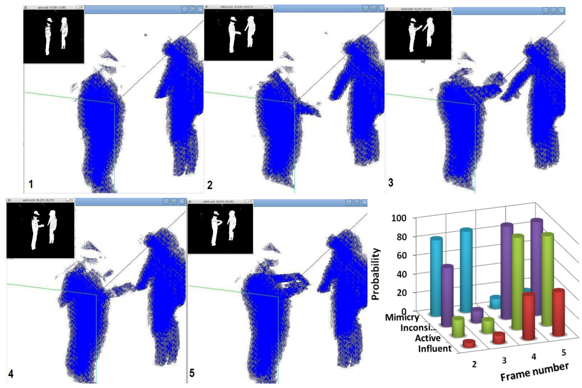

Fig. 6. an exemplary short sequence (5 sec. length, labeled from 1 to 5). The histogram represents the output for each IB for the seconds 2 to 5.

For the purpose of classification, the obtained LMA parameters from each frame are fed to the proposed IB models. Fig. 6 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.

Fig. 7-a) presents the *Indicator* model results. As seen, the classification results need a maximum of three frames to converge. In Fig. 7-b), which present the *Interest* model results, the convergence is faster, because it only depends on the current observed LMA state in an individual-based approach.

Fig. 7-c) presents the *Empathy* model results. The graph is divided in two parts. The first part, corresponding to the 33 first frames, presents the results based on head-space feature (nodding), and the rest are based on the copying body part motions features. The first part shows faster convergence. It means, the knowledge of the other person at time t-1, to estimate the states, makes convergence slower.

Fig. 7-d) presents the *Emphasis* model results. Most of parts the classification results converge to the ground truth. Only a few frames diverge from the ground truth signal (78^{th}, 79^{th} frame), because the states was changed very fast.

The accuracy for the IBs are; Indicator 71%, Interest 92%, Empathy 77% and Emphasis 71%. Thus overall accuracy of the IB model is 77.75%. In terms of comparing the works with the state of the art, there is a work by Pentland's group in (Dong et al. [2007]) which presents several analysis by different classifiers to estimate the IBs. The best overall results was 75%, however they used not only body motions, but also speech signals.

5. CONCLUSION AND FUTURE WORKS

In this paper, the existent interrelations between body part motions, which play an important roles to understand IBs, were analysed in social context. For obtaining the goal, there is a couple of problems. Thus, we propose

a)
b)
c)
d)

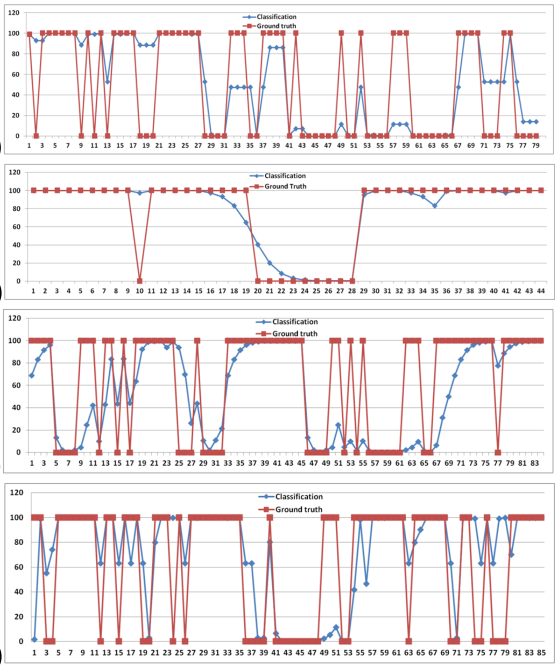

Fig. 7. Classification result: the probability of the person being in a) *Influent* state in each frame (*Indicator* model), b) *Active* state in each frame (*Interest* model), c) *Mimicry* state in each frame (*Empathy* model), d) *Inconsistent* in each frame (*Emphasis* model).

to use; first, LMA components as our observation data (the analysis through LLFs are very complicated to understand, and also it reduces the losing information during the transformation of LLFs to IBs.), and secondly, DBN for modeling and classification process (we need the flexibility of DBN to define and implement the interrelations between variables.).

The interrelations between body parts motions in different IBs were analysed and modeled by Bayesian framework. The results were proved the expected relations between IBs and LMA as were presented in the experiment's section. In the section of discussions, the outputs of the IB's models, were analysed, and the evidences proved that those interrelations between body parts motions play an important role to estimate the IBs.

For future work we will develop models encompassing signal features instead of LMA parameters as observations, to compare with actual results. To further improve of this work we also intent to use Relationship component to model interaction of people with the environment. The model will be scaled to estimate social roles as described in Pentlands work. We will develop a system that allows the model to improve its update rate.

6. ACKNOWLEDGMENT

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