Measuring Human movements in the wild for HRI Contexts

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***Abstract*—Body movements are one of the main cues used in HRI. Despite the fact that body movements have a mechanist part, measuring it cannot be achieved as objectively as expected. Inherent variability (inter and intra personal variability, cultural meaning dependency, etc.) is hard to model and needs data driven approaches. We give some examples about our works in gestures analysis in developing an effective gesture-based robot controller.**

Keywords—human behavior; HRI; gestures; physiology; model driven analysis, data driven analysis

I. Introduction

Human Robots Interactions (HRI) is a hybrid filed mixing many domains including engineering, physics, social sciences, neurosciences, etc. As such, research in HRI rely simultaneously on exact models and experimental approaches in developing interaction frameworks, theories and practical systems. Indeed and for the "R" part in HRI, measurements and procedures are known to be exact and objective. Models in these fields are enough known allowing quantitative accurate observations that can be measured repeatedly supporting the original models. Robots are controllable (most of the time) and observable agents. Their dynamics can be derived analytically allowing close form descriptions, i.e. the system can be described by equations. In psychology and social sciences the situation is different: the object of studies, namely humans, is much less known. Scientists in these areas are lacking in terms of accurate models compared physicists and engineers. Indeed, humans can be seen as high dimension multivariate systems, with complex dynamics, preventing from having complete explanatory models. This leads to qualitative approaches, where only isolated aspects (and most of the time related indirectly to the object of investigations) are considered.

The lack of knowledge combined with the poorness of analysis tools in human behavior analysis sounds like 'egg-chicken' problem. This situation is even worst when experiments are performed in real life conditions. Indeed, to obtain realistic observations, experiments in real world are needed; unfortunately, the control of experimental conditions is almost impossible out of laboratories, leading to higher difficulty and complexity in analysis and understanding.

In the recent years, more powerful and more adapted statistical methods have been introduced in behavioral sciences. Unsupervised analysis, latent modeling or data driven approaches for instance, have shown good properties in supporting more complexity allowing delivering more quantitative insights.

In our recent works about body movements' analysis, we focused on the "mechanist" part of behavior. This was supposed to be the easiest part as it is observable directly, it is of low dimensionality and thus, to some extent, objectively measurable. We showed how advanced statistical modeling could help in developing effective interfaces and also to give new insights about body movements/physiology relationships. We started with developing iconic gestures-based interface to control mobile robots. We showed that the main issues in such interfaces are related to:

1- Inter and intra personal variability,

2- Gestures segmentation

We solved the first issue using classical supervised machine learning tools, namely SVMs. For the second issue, we moved towards data driven and unsupervised techniques (change point model detection) in order to extract meaningful gestures present among inconsistent body movements (gesticulations). Another use of specific statistical tools was done to understand the relationships between body movements and some physiological signals. Here as well, our data driven approach allowed us to find out objectively how electro-dermal activity can predict movements.

In the following, we give the headlines of our approaches and more importantly, we discuss the difficulties we faced and the ways we circumvent it. We give also our recent line of research, which introduces some a priori "mechanist" knowledge to master the interpretation space.

II. Gestures, gesticulations and body movements in the wild

A. Model driven data analysis

A large part of communication among humans and behaviors humans can exhibit are conveyed through nonverbal channels. Typically, facial expressions, body postures and gestures are considered complementary information to make speech messages more effective. Even if this assertion is still under debate, in HRI and with the lack of efficient speech recognition and understanding systems, gestures the usual candidates allowing naïve users to control robots through iconic gestures. The later are studied since the 40's under different aspects. Indeed, David Efron has initiated the analysis and classification of gestures for ethnography purposes. He postulated four main features to describe gestures: 1) spatio-temporal aspects, 2) the topographical relationships between the interacting persons, 3) The linguistic content and 4) gesticulations.

In our research, we focused on a class of gestures, namely, Emblematic/autonomous/symbolic gestures. These arm movements arm are usually accepted as face-to-face social gestures conveying self-contained semantic meanings. In other words, they do not need any additional information to be understood. These gestures are known to be structured and can be described through arm motion (joints position). The sequences have three main phases (pre-stroke, stroke and post-stroke), corresponding respectively to the preparation of the gesture; its execution and the return back to a rest position. On the basis of this structure, we developed a recognition system [1,2]. For this system, we made the assumption that the iconic gestures are segments that can be isolated, i.e., the pre-stroke and the post-stroke can be extracted. Accordingly, we developed a segmentation routine based on this assumption. We showed that controlling a robot using iconic gestures is feasible using a simple SVM to classify accurately a set of five iconic gestures. The system worked well in lab conditions, where people were instructed to be careful in performing the gestures. Unfortunately, the system failed in real life conditions: the robot was unable to extract meaningful gestures when other body movements were performed (gesticulations for instance).

B. *Segmenting human gestures*

To separate between iconic gestures and gesticulations (respectively structured movements and chaotic ones), we considered arm movements are multivariate time series. According to our initial hypotheses (structured *vs* unstructured), we hypothesized statistical structure changes between gesticulations and gestures. That is to say, we considered gesticulations and iconic gestures as random variables drawn from different distributions. Following this hypothesis, we quantized the multivariate time series and we applied a T-test CPM (change point model) technique.

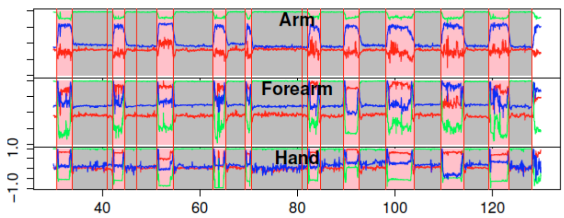

Fig. 1. Right arm movements segmentation

The developed technique [3] allowed us a high accuracy in segmenting upper body movements and thus good rates in recognizing robot controls. Through this work, we showed that a simple discrimination based on a weak hypothesis (distribution difference) is enough to perform meaningful segmentation.

III. Physiciological Signals in the Wild: What We Can Learn from Electrodermal Activity

Electro-dermal activity (EDA) or equivalently the skin conductance (SCR) are known as good candidate features to measure the stress when performing interactions or experiencing stressful situations. Unfortunately, EDA is observed also when physical efforts are performed: moving arms, walking or just standing induces EDA, which has to be considered as artifacts. Following that, it has been highly recommended to measure EDA-SCR in static situations, mainly with fixed arms as the sensors were placed on the wrist, the hand palm or on feet. In real life situations, humans are moving, if not continuously (walking or discussing), at least the static position does not last for long times. Limiting studies to just static situations seems to be too strong and prevents from observing realistic behaviors. The second point deals with stimulations. Except with movies, most of research uses predetermined stimulus. That is to say, photos, sounds or other physical activities that produce high-level emotions. These lab conditions cannot be applied to real life. In our work, we aimed at understanding the relationships between EDA and movements in real stressful conditions: PhD students' public defenses were recorded and analyzed using the extreme values theory (EVT). We confirmed the existence of EDA/movement artifacts. More important, we found out that EDA can predict movements: people perform movements after EDA increases (likely to lower the stress). In this work [4], we didn't use any model except the fact that EDA peaks are rare events with a tail-shaped statistics. The data showed us a phenomenon no observed before.

IV. Conclusions and Recommendations

In our work concerning human movements analysis, we showed that classical approaches cannot be applied to real life conditions and data driven techniques are more suitable to perform recognition tasks and more. We are pursuing this trend with the inclusion of minimalistic mechanist hypothesis: namely, we consider the movement as originated by latent forces, themselves issued by compact neuro-controllers.

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