How Social Signal Processing (SSP) Can Help Assessment of Bonding Phenomena in Developmental Psychology?

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Abstract. In the field of biology, the study of bonding has been renewed by the discovery of non genetic transmission of behavioural traits through early mother-infant interaction and the role of stress hormones and ocytocin. However, the study of early interaction is complex and Social Signal Processing (SSP) can help in addressing some issues. Based on works from our group, we will show data from diverse sources (e.g. experiments, home movies) showing how SSP was used to address synchrony between partners (e.g. infant, child, care giver, agent) and characteristics that participates to interpersonal exchanges (e.g. motherese, emotional prosody or faces).

1 Introduction

Recent advance has shown that human learning and cultural evolution are supported by paradoxical biological adaptation. We are born immature; yet, immaturity has value: "Delaying maturation of cerebral cortex allows initial learning to influence the neural architecture in ways that support later, more complex learning" [28]. Early learning appears to be computational [22], to be based on perceptual-action mapping (meaning that it is supported by brain circuits linking perception and action). Learning is also social and supported by skills present in infancy: imitation, shared attention and empathic understanding [28]. The paradigmatic situation of very early empathic skills is described as bonding that occurs in all species and starts at birth. Assessment of early interaction between an infant and his/her caregiver remains challenging as it requires considering both partners and mutual influences they provide during interaction.

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In this paper, our aim is to show that SSP can help in addressing some issues. Based on works from our group, we will show data from diverse sources (e.g. experiments, home movies) showing how SSP was used to address synchrony between partners (e.g. infant, child, care giver, agent) and characteristics that participates to interpersonal exchanges (e.g. motherese, emotional prosody or faces). To do so, we will first describe the bonding phenomena and consider how recent developments in the field of biology have renewed its core importance during development. Second, we will review computational modelling of interpersonal synchrony. Third, we will show that automatic detection of non-verbal cues of interpersonal synchrony may help addressing the complex issue of the emotional implication in interpersonal exchange. Finally, we will propose some prospects in new methods and tools for the study of children development.

2 Description of the Bonding Phenomena

The first evidences of the bonding phenomena came from two sources in the fifties: (1) ethologists studying early development and interaction showed in birds and monkeys, the printing phenomenon; (2) child psychoanalysts studying the impact of severe deprivation and mother-infant early separation described infant depression and its reversibility by providing infants warm and individualised care. Later, Bowlby proposed the attachment theory and provided a theoretical background for many studies trying to understand consequences of early adversities in infants. Early infant-caregiver interaction was then specifically studied to understand bonding, attachment and early development [26].

Despite the pioneering efforts of Denenberg, who first showed the non-genomic transmission of behavioral traits in animals when studying early separation [12], we only recently understood the biological implications of early stress. Using rodent models, Meaney and Champagne showed that early stress, maternal care and stress during the gestation affected the development of future generations of rats through the hypothalamus-pituitary axis (HPA) and epigenetic modifications. These modifications could be transferred from generation to generation and were independent of an animal's genetic inheritance. The following briefly lists some important points learned from these experiments: 1) Early experience has a long-term effect on behavior and the biological system, especially when the mother and offspring are separated or when the quality of maternal care varies dramatically [23]; 2) Certain early experiences can affect future generations, providing a non-genomic mechanism for the transmission of behavioral traits [16]. It appears that maternal care affects development through a behavioral program and the future adult's pathological responses to stress. The quality of maternal care influenced the stress response HPA axes of offspring [23] and greatly influenced the epigenesis in the following generations (through DNA epigenomic marking) [44]. Furthermore, naturally occurring variations in maternal behavior are associated with differences in estrogen-inducible central oxytocin receptors, which are involved in pro-social behaviors [8]. Oxytocin appears to enhance both maternal as well as affiliative behaviors and is considered as the bonding hormone. These developments have pushed developmental psychologists to study early interaction not only as the addition of two behaviors but rather as a single phenomenon with a dialogue between two partners engaged in behavioral and emotional exchange. Developmental psychologists give now importance to rhythm, synchrony and emotion, regarded as key expression of proper early interaction [15]. However, the study of synchrony and emotion in children interacting with a partner or a caregiver is complex and SSP can help in addressing some issues.

3 Computational Modeling of Interpersonal Synchrony

Synchrony refers to individuals' temporal coordination during social interactions [11,20]. The analysis of this phenomenon is complex, requiring the perception and integration of multimodal communicative signals [11]. The evaluation of synchrony has received multidisciplinary attention because of its role in early development [14], language learning [18] and social connection [19]. Initially, instances of synchrony were directly perceived in the data by trained observers. Several methods have been proposed to evaluate interactional synchrony, ranging from behavior micro-analysis [6] to global perception of synchrony [3]. Synchrony has now captured the interest of researchers in such fields as social signal processing, robotics and machine learning [21,33].

3.1 Fully Automatic Measures of Movement Synchrony

To exploit synchrony cues in human-machine interaction, automatic techniques can be used to capture relevant social signals and assess movement synchrony in human-human interactions. This studies aim at measuring the degree of similarity between the dynamics of the non-verbal behaviors of dyadic partners. The goals of these studies are generally divisible into two categories: (a) compare the degree of synchrony under different conditions (e.g., with or without visual feedback) [39,42] and (b) study the correlation between the degree of synchrony and an outcome variable (e.g., friendship, relationship quality) [1,34].

The first step in computing synchrony is to extract the relevant features of the dyad's motion with motion-tracking devices [2], image-processing techniques (tracking algorithms, image differencing) [9,42] or physiological sensors [42]. After extracting the motion features, a measure of similarity is applied. Correlation is the most commonly used method to assess interactional synchrony [1,34]. A time-lagged cross-correlation is applied between the movement time series of the interactional partners using short windows of interaction. Another method to assess the similarity of motion of two partners is recurrence analysis [35]. Recurrence analysis assesses the points in time that two systems show similar patterns of change or movement, called "recurrence points". Spectral methods constitute an interesting alternative to temporal methods when dealing with rhythmic tasks. Spectral methods measure the evolution of the relative phase between the two partners as an indication of a stable time-lag between them [31,37]. Spectral methods also measure the overlap between the movement frequencies of the partners, called cross-spectral coherence [9, 36, 37] or power spectrum overlap [31].

A critical question when attempting to detect dependence relationships between features is the level of significance of the synchrony metrics. A well-spread method consists of applying surrogate statistical testing [2,9,36,40]. Video images of dyadic partners are isolated and re-combined in a random order to synthesize surrogate data (pseudo-interactions). Synchrony scores are assessed using the original and surrogate datasets. The synchrony scores on the surrogate dataset constitute a baseline for judging for the dyad's coordination. Fully automatic measures of movement synchrony are subject to several criticisms in the context of studying naturalistic interaction data. First, the measures provided by these methods are mostly global and do not shed light on what happened locally during the interaction; they do not provide a local model of the communication dynamics. Second, the importance of speech and multimodality is often concealed in these methods. Third, these methods are suitable for analyzing a database but do not provide direct insights on how to equip a machine with such coordination skills.

3.2 Modeling Communication Dynamics

Given these criticisms, many in the field adopted the alternative practice of modeling the timing and occurrence of higher-level behavioral events such as smiles, head gestures, gazes and speaker changes. These behavioral events can be either extracted from a human-annotated database or predicted from low-level signals automatically extracted from data. These methods arise from a great interest in identifying the dynamical patterns of interaction and characterizing recurrent interpersonal behaviors.

Machine learning methods offer an interesting framework for the exploration of interactive behaviors. A key challenge is proposing models with the content and temporal structure of dyadic interactions. Various sequential learning models, such as Hidden Markov Models (HMMs) or Conditional Random Fields (CRFs), are usually used to characterize the temporal structure of social interactions. Messinger et al. employ related techniques for the understanding of communicative development, which is characterized by mutual influences during interaction: infants and parents influence and respond to one another during communication [29]. In section 3.3, we will further develop these prospects in children with autism.

Among interpersonal behaviors, the prediction of turn-taking and back-channels has been largely studied in the perspective of building fluent dialog systems. The central idea is to develop "predictive models of communication dynamics that integrate previous and current actions from all interlocutors to anticipate the most likely next actions of one or all interlocutors" [32]. The purpose of the turn-taking prediction is to accurately predict the timing between speaker transitions and the upcoming type of utterance (speaker holding the floor, speaker changes) as it occurs in human-human interactions [43]. Back-channel behavior assures the speaker that the listener is paying attention and is in the same state in the conversation [41]. Several teams have investigated how the speaker behavior triggered listeners' back-channels [30].

3.3 Interaction and Communication of Children with Autism Spectrum Disorder and Typically Developing Children

Here, we present two examples of the use of computational analysis to describe interaction and communication of children with autism. In the first experiment, we asked children with autism and TD controls to build a clown in three different situations: (1) the child imitates the speech therapist; (2) the child follows vocal instruction; (3) the child gives vocal instructions. Using automatic extraction of speech turn taking, gestural turn tacking and synchronized motion coupled with machine learning, we found that features characterizing the rhythm of the therapist and the duration of his gestural pauses were particularly adequate to predict the child clinical group. We also found that the performance in the tasks also depended on the age of the child, especially when the child gives instruction to the therapist. The volume of speech interventions, the duration of the therapist interventions and the duration of the therapist gestural pauses were found to be predictive of the age of the child in this task [10].

In the second example, we aimed to assess whether taking into account interaction synchrony would help to better differentiate autism (AD) from typical development (TD) in family home movies (HM) of infants aged less than 18 months. An integrative approach was proposed to explicitly consider the interaction synchrony of behaviors. We estimated transitions between behaviors of the infant and the parent by analyzing behaviors co-occurring in a 3s window. Assuming a Markovian process, we used a maximum likelihood estimation to estimate the probability of each interactive pattern, resulting in bi-gram models characterizing the temporal structure. We also considered the two directions of interaction (Parent→Infant and Infant→Parent). Compared to TD children, infant with AD exhibit a growing deviant development of interactive patterns. Parents of AD did not differ very much from parents of TD when responding to their child. However, when initiating interaction, parents use more touching and intense stimulation as early as the first semester [38].

4 Automatic Detection Non-verbal Cues of Interpersonal Synchrony

As said previously, early interaction is not only based on behavioural cues but also on emotional cues. These appeared to be crucial although assessment in infant and CG is complex. Developmental psychologists have shown that motherese (the way CG talk with their infant) has specific characteristics and plays a key role in early interaction and language learning. Here, we summarized two aspects of automatic detection of emotion based either on audio or video extraction in the context of human-robot interaction and home movies.

4.1 Facial Expressions Assessment through Human-Robot Interaction

We are interested in understanding how babies learn to recognize facial expressions without having a teaching signal allowing to associate a facial expression to a given abstract label (i.e the name of the facial expression 'sadness', 'happiness'...). Our starting point was a mathematical model showing that if the baby uses a sensory motor architecture for the recognition of the facial expression then the parents must imitate the baby facial expression to allow the on-line learning. A first series of robotics experiments showing that a simple neural network model can control the robot head and learn on-line to recognize the facial expressions (the human partner imitates the robot prototypical facial expressions) is presented. We emphasize the importance of the emotions as a mechanism to ensure the dynamical coupling between individuals allowing to learn more complex tasks.

Using the cognitive system algebra [17], we showed that a simple sensory-motor architecture based on a classical conditioning paradigm could learn online to recognize facial expressions if and only if we suppose that the robot produces first facial expressions according to his internal emotional state and that next the parents imitate the facial expression of their robot allowing in return the robot to associate these expressions with his internal state.

4.2 Experimental Set-Up

Using a minimal robotic set-up (Figure 1), we adopt the following experimental protocol: In a first phase of interaction, the robot produces a random facial expression (sadness, happy, anger, surprised) plus the neutral face during 2s, then returns to a neutral face to avoid human misinterpretations of the robot facial expression during 2 sec. The human subject is asked to mimic the robot head. After this first phase lasting between 2 to 3 min according to the subject "patience". The generator of random emotional states is stopped. If the N.N has learned correctly, the robot must be able to mimic the facial expression of the human partener. The computional architecture (Figure 2) allows to recognize the visual features of the people interacting with the robot head and to learn if these features are correlated with its own facial expression.

4.3 Neural Network Model

We use a visual system independent from face framing. The visual system is based on a sequential exploration of the image focus points (Figure 3). The focus points are the result of a DOG filter convolved with the gradient of the input image. This process allows the system to focus more on the corners and end of lines in the image for example eyebrows, corners of the lips, but also distractors (hair, background). Its main advantages over the SIFT (Scale Invariant Feature Transform) [24] method are its computational speed and a fewer extracted focus points (the intensity of the point is directly its level of interest).

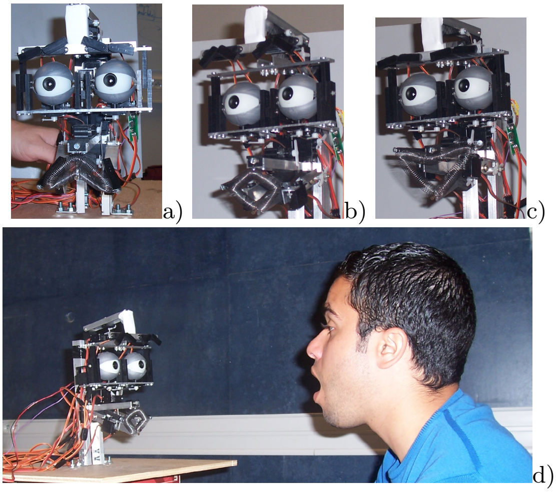

Fig. 1. Examples of robot facial expressions: a) sadness, b) surprise, c) happiness. d) Example of a typical human / robot interaction game (here the human imitating the robot).

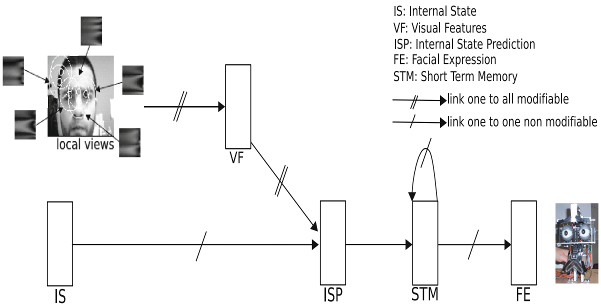

Fig. 2. The global architecture to recognize facial expression and imitate. A visual processing allows to extract sequentially the local views.

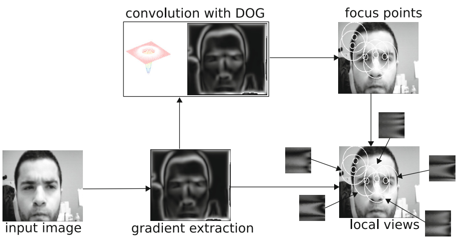

Fig. 3. Visual processing: This visual system is based on a sequential exploration of the image focus points

One after the other, the most active focus points of the same image are used to compute local views: either a log polar[1] transform centered on the focus point is performed to obtain an image more robust to small rotations and distance variations and his radius is 20 pixels, and gabor filters are performed (robust to rotations and distance variations). The features extracted for the convolution between the gabor filter and the focus point are the mean and the standard deviation.

This collection of local views is learned by the recruitment of new neurons (visual features). Of course, there is no constraint on the selection of the local views. This means that numerous distractors can be present (local views in the background, or inexpressive parts of the head). Thereforre, distractors can be learned. Nevertheless, the architecture will tend to learn and reinforce only the expressive features of the face (Figure 2). In our face to face situation, the distractors are present for all the facial expressions so their correlation with an emotional state tends toward zero.

A simple conditioning mechanism (the Least Mean Square rule [45]) is able to associate the visual features with the internal state. A sensory-motor architecture learn online to recognize facial expressions if and only if we suppose that the robot produces first facial expressions according to his internal emotional state and that the parents imitate the facial expression of their robot allowing in return the robot to associate these expressions with his internal state.

Arbitrary, a limited amount of time is fixed for the visual exploration of one image. The system succeeds to analyse 10 local views on each image. It is a quite small number of points but since the system usually succeeds to take 3 to 4 relevant points on the face (mouth, eyebrow).Yet, it is enough in most cases and it allows to maintain real time interaction (3 to 5 images/second) in order to test our model.

After learning, the robot head can imitate the human's facial expression and the focus points are associated to each facial expression i.e these focus points vote for the recognition of a given facial expression. Each facial expression is mainly characterized by a specific set of focal points corresponding to local areas on the face which are relevant for the recognition of that expression. For example, some local view around the mouth (lip) characterize the "happyness" facial expressions, some others around the eyebrows characterize the anger facial expression. Figure 4 shows that the model can generalize to people who were not present during the learning phase. A possible explanation for the bad result concerning sadness is that the people have difficulties to display sadness without a context. Each partner imitating the robot displays the sadness in a different way.

Our robot learns thanks to the interaction with a human partner. Our model has allowed us to show that in order to learn online to recognize the facial expressions, the learner must produce facial expressions first and be mimicked by his/her caregiver [4]. The system proposed had no real interaction capability dur-

[1] The local polar transform increases the robustness of the extracted local views to small rotations and scale variations.

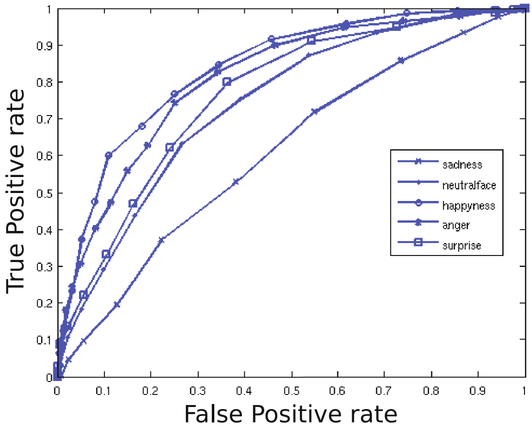

Fig. 4. Generalisation to new faces: After 20 persons interacted with the robot head (learning phase), the robot had to imitate new persons never seen

ing the learning phase since this phase was completely predefined. In conclusion, this work suggests the baby/parents system is an autopoietic social system [27] in which the emotional signal and the empathy are important elements of the network to maintain the interaction and to allow the learning of more and more complex skills as the social referencing[2] [5].

4.4 Motherese: An Emotional Based Process for Sustaining Mother-Infant Interaction

Given the role of motherese in early interaction of typically developing children [13], we aimed to explore whether or not this emotional prosody was implicated in a different way in early interaction of infant who will later develop autism. To do so, we developed an automatic algorithm based on prosodic features to classify motherese versus other speech in Home Movies (HM) [25]. We then assessed the course of infants' responses to parents' vocalisation in the same HM data base described earlier. We found: that parents of infants developing autism displayed more intense solicitations rich in motherese; that motherese increased infant responses towards people and infant receptive behaviours; that fathers of infants developing autism assumed a greater part in vocalisations addressed to infants, and appeared to increase infant intersubjective responses and active behaviours. We conclude that parents of infants who will later develop autism change their interactive pattern of behaviour by both increasing motherese and father's commitment as they improve infant's social responses. Taken together

[2] The ability to recognize, understand, respond to and alter behavior in response to the emotional expressions of a social partner.

these results stress that parents are aware of the pervasive development of their child, and that they try to adapt long before diagnosis are given [7].

5 Conclusion

We conclude that SSP can help to address some of the issues related to the study of early interaction. SSP can be used for several purposes such as modelling, assessing synchrony between partners and characterizing specific sues that participates to interpersonal exchanges. SSP may also be of interest for developing specific tools with human-like abilities to stimulate social behaviors in a controlled context.

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