How Imitation Boosts Development: In Infancy And Autism Spectrum Disorder Read Online

Impairments in imitation are present in young children with autism spectrum disorders ASD, but the onset of these impairments is unknown. The present study investigated the developmental trajectories affiliated with various types of imitation.

Imitative performances in infancy were observed in a prospective design, and retrospectively compared between ASD and typically developing TD infants. View PDF. Save to Library. Create Alert. Launch Research Feed. Share This Paper. Devon N. Messinger Journal of autism and developmental disorders Figures from this paper. Citations Publications citing this paper. Messinger Psychology, Medicine Journal of autism and developmental disorders References Publications referenced by this paper.


Rogers, S. Hepburn, T. Stackhouse, E. Wehner Medicine, Psychology Journal of child psychology and psychiatry, and allied disciplines Thus, we hypothesized that coupling the number of neurons needed to learn from VF with a novelty detector would help in achieving person recognition.

To do so, the novelty detector produces feedback, since the robot needs mechanisms of self-assessment for regulating and modulating learning. As a consequence, the robot is able to evaluate its learning. This mechanism, based on prediction error, can be used with sensory-motor coupling and is detailed on Fig. Prediction error provides a measure of learning progress.

In our case, we hypothesized that the sensory-motor architecture learns connections between perceptions and actions and the self-assessment prediction error allows the robot to detect a new event in our experiments, a new partner. The novelty detection coupling b allows the robot to detect novelty in the visual sensations.

Three principles are used: i prediction error; ii derivative of error; iii detection of rising edge novelty. The robot learns the sensory-motor contingency of a given strategy by learning to predict the current sensation from the previous perception. To evaluate robotic learning, we performed three experiments using the same computational learning architecture in different contexts Fig.

Key experiment differences included changing partners child, adult or avatar, motor imitation tasks involving arms or face and robotic platforms. In Experiment 1, the robot Nao, interacted with a human partner - either a typically developing TD child, a child with autism spectrum disorder ASD, or an adult during a motor imitation task 5 postures.

After the learning phase, the results show that Nao is able to accurately recognize the interactive agents in a subsequent encounter. In Experiment 2, we changed both the imitation task 5 facial expressions and robotic platform Robot head and obtained a similar transfer for person recognition after the learning phase.
The current experiments used the same learning architecture and varied the learning context: Experiment 1, top posture imitation between the robot Nao and human partners; Experiment 2, middle facial imitation between Robot Head and human partners; Experiment 3, lower posture imitation between the robot Nao and avatars partners.

Experiment 1 used a motor imitation task 5 postures, see supporting online materials, Figure S1 between a Nao robot and a human partner.

N activities during the learning phase are shown in Fig. The number of neurons needed to learn in the Visual Feature N. When a new participant is introduced during the learning phase, the novelty module shows an important activity green line and a brief synchronous hit occurs in the Person Recognition N. To test how the architecture developed person recognition, we presented different images per participant to the system in four conditions using two dichotomous contrasts: i images shown randomly or not and ii images previously watched during the learning phase or not.

In terms of recognition performance rates Fig. Recognition rate per participants and conditions are shown in Figure S2. Four recognition scores were highly correlated Fig. Only 5 TD children vs. On average, recognitions scores were significantly better for adults vs. TD children.

The number of neurons needed to learn from the Visual Features N. Experiment 2 tested the generalizability of our modeling in another interactive context.

We changed the task and the robotic platform by using an expressive robot head in an emotional interaction paradigm.

The robot head learned through a motor facial imitation task 4 emotional facial expressions plus a neutral face; see online Figure S3 with 25 adult participants who imitated the facial expressions of the robotic head. N activities during the learning phase was similar to those in Experiment 1 see Supporting Online Material, Figure S4. The architecture was able to recognize on average Recognition rate per participant and condition are summarized in supporting online material Figure S5.

Experiment 3 was carried out to control for unexpected visual cues that may have contributed to recognition scores e. To achieve this goal, Nao was imitated by a set of 12 avatars that were highly similar in their visual presentation white humanoids but with specific traits that we systematically manipulated length or width of the arms, head or body sizes, see supporting material, Figure S6.

The results showed that the N. N activities during the learning phase were similar to those in Experiment 1 see Figure S7. Recognition rate per participant and condition are summarized in supporting material Figure S8. In all three experiments we used developmental robotics and computer modeling to implement a test of the idea that preverbal mutual imitation of actions between infant and caretaker may support a social identity function.

Based on prior human infant work 13, 14, we predicted that imitative experiences during robot-human interaction would enable the robots to recognize a human partner that the robot had already encountered. The results accord with this prediction. During mutual imitation episodes, the robot learns signature actions, postures and facial expressions and an emergent property obtains person recognition. Our model used a sensory-motor architecture based on neural networks Hebb conditioning 22, 23, 24 coupled with an auto-evaluation mechanism based on prediction error to detect a new social partner perceptual novelty.

Five points are relevant to theories of robotic and human learning and development. First, the architecture enabled the simultaneous development of perceptual, motor and cognitive abilities. Second, the current work fits with the idea that the representation of the body is important to social-cognitive development.

To bring greater precision to this general idea, we used robots because we could implement our model in a rigorous way by strictly controlling and specifying the behavior of robots.

From our point of view, a different body involves a different learning. The fundamental fact is that infants and robots do have bodies and these play a significant role in their initial social learning and development, as illustrated in the current experiments and recent infant neuroscience theory and data. Indeed, our model needs a sensory-motor internal state to proceed with imitation learning. The robot is able to learn because it acts in the environment and with others. The robot connects what it sees with what it does corresponding to a perception-action mapping.

In addition, the results show that a mirroring mechanism, the sensory-motor architecture and a self-evaluation mechanism error prediction and evaluation are sufficient to develop an autonomous robot in which imitation is an important element in the interaction and allows the learning of a complex ability such as person recognition. Previous work on interpersonal interaction has highlighted the centrality of motor dynamic similarity in joint action 32 and in human robot interaction Other studies in robotics 34, 35, 36 have discussed the role of learning and social referencing.

However, the current work goes further by proposing a developmental approach in which a real self-supervised developmental sequence can emerge. We designed a model allowing learning through interaction by using low level features and minimal knowledge to avoid the symbol grounding problem the problem of how symbols get their meanings. Third, the child–robot interactions involved imitative encounters.

Developmental scientists working with human infants 7, 11, 38, have pointed out that mutual imitation games are a common occurrence among infants and caretakers and provide a rich learning experience not only because they include structural matches, but also because they include a temporal component. Interpersonal temporal synchrony of the type occurring in mutual imitation is now considered as a social signal per se 5, 6 and has been associated with both neural 39 and hormonal changes in humans 40. The robot would not have developed without the help of the human agent caregiver.

Our computational modeling served to render this kind of social learning more precise and quantifiable than is often the case within developmental and clinical psychology. Fourth, consistent with work showing that infants react to being imitated in special behavioral and affective ways, exhibiting
a distinctive infant neural response to having their behavior copied reduction in mu rhythm in the EEG 42, the human partner in the current robot experiments was considered as a mirror during the learning phase.

Consequently, the robot could learn to connect what it saw with what it did. When the sensory-motor architecture was used in this learning context and coupled with the novelty detector, this was sufficient to develop new autonomous behaviors person recognition.

Our current model and experiments involved typically developing children in child-robot interaction, children with ASD in child-robot interaction, as well as adult-robot interaction and avatar-robot interaction. This suggests that the architecture allows for generalized learning across a broad range of agents and interactive participants.

In summary, the experiments illustrate that i) robots learn to recognize individuals from imitating adults, children with autism and other agents; ii) robots can be used as tools for modeling cognitive development, based on developmental theory, confirming the promise of developmental robotics; iii) in our computational model, person recognition spontaneously emerges through imitation learning, intercorporeal mapping and statistical learning.

Participants characteristics involved in experiment 1 and 2 are given in supplementary Table S1. Typically developing TD children were recruited from several schools in the Paris area.

They were matched to the children with ASD with respect to their developmental ages and genders. The developmental age was assessed using a standardized cognitive assessment.

Also, we included a group of children with ASD to address whether peculiarities in social interaction that are impaired in children with ASD 46 would affect the recognition results.

Adults participating in experiment 1 and 2 were University students from Medical and Engineering schools. Each participant has performed the experiment with the robot only one time. All the parents or participants received written and oral information on the experiment and gave written consent before their participation or the participation of their child.

All experiments were performed in accordance with relevant guidelines and regulations. We adopted a developmental approach whereby a robot learned through interaction with a partner. Posture recognition was learned autonomously using a sensory-motor architecture through an imitation game between the partner and the robot. Figure 2 middle column shows an overview of the experimental design for all the experiments. During the learning phase, the robot produced a random posture selected from a defined set of postures and the participant imitated the robot; then, the robot mapped what it did to what it saw.

The architecture enables learning without explicit teaching signals see details below. During the validation phase, the robot then had to imitate the posture of the partner who now was leading the imitation interaction.

During the first phase, the robot learns the task, but also records all the images. Consequently, a database is created to perform offline processing. Each image was annotated with the response of the robot during the online learning.

After the mutual imitation encounter, we presented for a second time each partner through a set of pictures for testing recognition see below. To show the generalizability of our sensory-motor approach whereby a robot learned through interaction with a partner. Posture recognition was learned autonomously using a sensory-motor architecture through an imitation game between the partner and the robot. Figure 2 middle column shows an overview of the experimental design for all the experiments. During the learning phase, the robot produced a random posture selected from a defined set of postures and the participant imitated the robot; then, the robot mapped what it did to what it saw.

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centered on the focus point is extracted: a log-polar transform was applied to obtain an input image or a vector more robust to the rotations and distance variations.

Figure 1a shows the sensory-motor architecture that enabled the learning, recognition and imitation of postures. The extracted local view around each focus point was learned and recognized by a group of artificial neurons VF visual features allowing online learning and in real time.

VF j is the activity of neuron j in the group VF. This model enables the recruitment to adapt to the dynamics of the input. The learning rule allows both one-shot learning and long-term averaging.

The modification of the weights W ij is computed as follows: Here, is the Kronecker symbol. When a new neuron is recruited, the weights are modified to match the input term a j t i. The closer the inputs are to the weights, the less the weights are modified. Conversely, the further the inputs are from the weights, the more the weights are averaged.

This learning rule enables the neurons in the VF group to learn to average the prototypes of postural features such as an arm. For the classification approach, only the local views for the person Fig.

The Widrow and Hoff rule 49 can be used to learn the image correctly if sufficient focus points can be found on the person during the period over which one image is explored. In our network, motor internal state prediction MISP associates the activity of the visual features VF with the current motor internal state MIS of the robot, a simple conditioning mechanism is used, the least mean square LMS rule. The modification of the weights w ij is computed as follows:

The short term memory STM is used to sum and filter over a short period. Novelty detection aims at identifying new or unknown data which differ from the normal data that the architecture was trained with. This process is performed by the identification of outliers in the stream of VF. ASD

The novelty detection is designed to distinguish the difference between prediction error caused by the model insufficiency and prediction error by novelty in the VF.

The self-evaluation mechanism allows the robot to regulate its learning by differentiating the sensory-motor associations which are known, unpredicted by the current system, or in progress. The novelty detection produces a rich signal that enables and triggers the learning of specific events. The novelty detection is computed from analysis of the prediction error, where changes may indicate some form of novelty.

This mechanism has been implemented as follows. The error t is computed as the difference between the predicted signal and the actual signal t . The rising edge is interpreted as the detection of a new event a new person interacting with the robot. In our model, the novelty detector is used to trigger the learning of new person postures. During learning by imitation, the architecture recruits for each participant an artificial neuron in the person recognition N.

As a consequence, the number of recruited neurons is equal to the number of participants N in a given experiment. This interaction is seen as a video sequence of thousands of images. To test how the architecture developed person recognition, we used the following protocol with images for each condition per participant presented consecutively in 4 conditions using two contrasts: images shown randomly or not; images previously watched during learning phase or not. Here, random refers to static images from a video sequence being shown in a random order.

This leads to 4 recognition scores per participant one per condition and 4 mean recognition scores per experiment one per condition. Given our learning architecture, we expected recognition scores under known conditions to be better than recognition scores under unknown conditions.

Also, we expected recognition scores under non random conditions to be better than recognition scores under random conditions as in the latter the system could not rely on STM N.

Using Matlab, standard statistics were calculated for each recognition score mean, standard deviation, range, minimum and maximum for each experiment. Statistical analyses were performed using R Software, Version 2.

We also calculated the number of subjects recognized per experiment with ratings superior than 10 times the response by chance.

To provide detailed assessment of whether the obtained recognition score was moderated by one of the two contrasts of the testing conditions [known pictures as opposed to unknown and pictures shown randomly as opposed to non-randomly], we used a general linear mixed model-GLMM with the recognition score as the variable to be explained.


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Rogers , S. Hepburn , T. Stackhouse , E. Wehner Medicine, Psychology Journal of child psychology and psychiatry, and allied disciplines Imitation from 12 to 24 months in autism and typical development: a longitudinal Rasch analysis. During this time, we have made some of our learning resources freely accessible.

Our distribution centres are open and orders can be placed online. Do be advised that shipments may be delayed due to extra safety precautions implemented at our centres and delays with local shipping carriers. It was Plato who famously stated that ‘imitation is dangerous because it stifles creativity, hampers the development of personal identity and disrupts the perception of other people as unique beings’.

There are some who still feel this way, and perhaps this explains why imitation has received less attention within the developmental literature than other human characteristics.

So why are humans able to imitate - from the very second they enter the world? Can it have positive effects? Can it help us interact with others better? Can it even make us feel better about ourselves and our ability to influence and interact with the world around us? In this book, a leading development psychologist explores the topic of imitation - looking at why we imitate and the possible benefits it might bring - in particular to those affected by Autism Spectrum Disorders.


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