The Free-play Sandbox: a Methodology for the Evaluation of Social Robotics and a Dataset of Social Interactions

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April 17, 2018

Abstract

Evaluating human-robot social interactions in a rigorous manner is notoriously difficult: studies are either conducted in labs with constrained protocols to allow for robust measurements and a degree of replicability, but at the cost of ecological validity; or *in the wild*, which leads to superior experimental realism, but often with limited replicability and at the expense of rigorous interaction metrics.

We introduce a novel interaction paradigm, designed to elicit rich and varied social interactions while having desirable scientific properties (replicability, clear metrics, possibility of either autonomous or Wizard-of-Oz robot behaviours). This paradigm focuses on child-robot interactions, and builds on a sandboxed free-play environment. We present the rationale and design of the interaction paradigm, its methodological and technical aspects (including the open-source implementation of the software platform), as well as two large open datasets acquired with this paradigm, and meant to act as experimental baselines for future research.

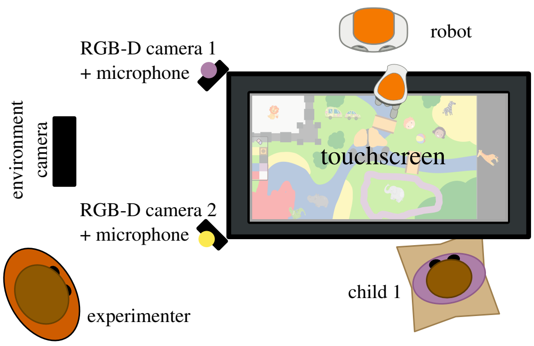

Figure 1: The free-play social interactions sandbox: two children interact in a free-play situation, by drawing and manipulating items on a touchscreen. Children are facing each other and sit on cushions. Each child wears a bright sports bib, either purple or yellow, to facilitate later identification.

1 The challenges in evaluating social interactions

1.1 Studying social interactions

Studying social interactions requires a social *situation* that effectively elicits interactions between the participants. Such a situation is typically scaffolded by a social task, and consequently, the nature of this task influences in fundamental ways the kind of interactions that might be observed and analysed. In particular, the socio-cognitive tasks commonly found in the literature of experimental psychology (and HRI) often have a narrow focus: because they aim at studying one (or a few) specific social or cognitive skills in isolation and in a controlled manner, these tasks are typically simple and highly constrained (for instance, an object handover task; a perspective-taking task with cubes, etc.). While these focused endeavours are important and necessary, we – as a community – also acknowledge that these interaction scenarios do not reflect the complexity and dynamics of real-world interactions Baxter et al. (2016), and we certainly observe a strong trend within our community towards capturing, interpreting and acting upon the rich set of naturally-occurring social interactions.

Specifically, we believe that further progress in the study of human-robot interactions should be scaffolded by socio-cognitive challenges that:

- are long enough and varied enough to elicit a large range of interaction situations;
- foster rich multi-modal interaction, such as simultaneous speech, gesture, and gaze behaviours;
- are loosely directed, to maximise natural, non-contrived behaviours;
- evidence complex social dynamics, such as rhythmic coupling, joint attention, implicit turn-taking;
- include a certain level of non-determinism and unpredictability.

The challenge lies in designing a social task that exhibits these features *while maintaining 'good' scientific properties* (repeatability, replicability, robust metrics) as well as good practical properties (not requiring unique or otherwise very costly experimental environments, not requiring very specific hardware or robotic platform, easy deployment, short enough experimental sessions to allow for large groups of participants).

In this paper, we introduce such a task, designed to elicit rich, complex, varied social interactions while being well suited for interactions with robots and supporting rigorous scientific methodologies.

1.2 Social play

Our interaction paradigm is based on free and playful interactions (free play) in a *sandboxed* environment: while the interaction is free (participants are not directed to perform any particular task beyond playing), the activity is both *scaffolded* and *constrained* by the setup mediating the interaction (essentially, a large table-top touchscreen). Participant engage in open-ended and non-directive play situations, yet sufficiently well defined to be reproducible and practical to record and analyse.

This initial description frames the socio-cognitive interactions that might be observed and studied: playful, dyadic, face-to-face interactions. While gestures and manipulations (including joint manipulations) play an important role in this paradigm, the participants do not typically move much during the interaction. Because it builds on play, this paradigm is also naturally suited to the study of child-child and child-robot interactions.

The choice of a playful interaction is supported by the wealth of social situations and social behaviours that *play* elicits. Most of the research in this field builds on the early work of Parten who established five *stages of play* Parten (1932), corresponding to different stages of development, and accordingly associated with typical age ranges:

1. **Solitary (independent) play**, age 2-3: Playing separately from others, with no reference to what others are doing.
2. **Onlooker play**, age 2.5-3.5: Watching others play. May engage in conversation but not engage in doing. True focus on the children at play.
3. **Parallel play** (adjacent play, social coaction), age 2.5-3.5: Playing with similar objects, clearly beside others but not with them (near but not with others.)
4. **Associative play**, age 3-4: Playing with others without organization of play activity. Initiating or responding to interaction with peers.
5. **Cooperative play**, age 4+: Coordinating one's behavior with that of a peer. Everyone has a role, with the emergence of a sense of belonging to a group. Beginning of "team work."

These five stages of play have been extensively discussed and refined over the last century, yet remain remarkably widely accepted as such. It must be noted that the age ranges are only indicative. In particular, most of the early behaviours still occur at times by older children.

Interestingly, these five stages can been looked at from the perspective of HRI as well. They certainly evoke a roadmap for the development of human-robot social interactions.

2 The Free-play Sandbox

2.1 Task

We have designed a new experimental task, called the *free-play sandbox*, that is based on free play interactions. Pairs of children (4-8 years old) are invited to freely draw and interact with items displayed on an interactive table, without any explicit goal set by the experimenter (Fig. 1). The task is designed so that children can engage in open-ended and non-directive play, yet it is sufficiently constrained to be suitable for recording, and allows the reproduction of social behaviour by an artificial agent in comparable conditions.

The free-play sandbox follows the sandtray paradigm Baxter et al. (2012): a large touchscreen (60cm × 33cm, with multitouch support) is used as an interactive surface (*sandtray*). Two children play together by freely moving interactive items on the surface (Fig. 2). A background image depicts a generic empty environment, with different symbolic colours (water, grass, beach, bushes...). By drawing on top of the background picture, the children can change the environment to their liking. The players do not have any particular task to complete, they are simply invited to freely play. Importantly, they can play for as long as they wish (for practical reasons, we have limited the sessions to a maximum of 40 minutes in our own experiments, see Section 5).

Capturing all the interactions taking place during the play sessions is possible and practical with this setup. Even though the children will typically move a little, the task is fundamentally a face-to-face, spatially delimited, interaction, and as such simplifies the data collection. For instance, during our dataset acquisition campaign (120 children, more than 45h of footage), the children's faces were automatically detected in 98% of the recorded frames (see Section 5).

Figure 2: Example of a possible game situation. Items (animals, characters...) can be dragged over the whole play area, while the background picture can be painted over by picking a colour.

2.2 Applications

Child-Child Interaction The free-play sandbox provides the opportunity to observe children interacting in a natural way in an open but framed setup. As the system can run on a single computer platform it can easily be deployed in the 'wild', in places where the children naturally interact such as classroom. The quantity and thoughtfulness of information logged allows to keep a track of every interaction happening around the game.

These advantages combined with the openness of the task proposed make this setup a powerful tool to observe and quantify a large spectrum of social behaviours expressed by children when interacting in a natural environment (might be interesting to add a list here). The compactness of the system makes it easy to compare data from different locations.

Child-Robot Interaction This free-play sandbox provides the opportunity to explore child-robot interactions in this open, real world environment as shown in Figure 1.

Depending of the focus of the study, two modes of control for the robot are available. If the interest is on evaluating a specific robot behaviour, the robot can be autonomously controlled using inputs from the different sensors. This setup allows to explore the impact of different social behaviours on the children independently of the 'game policy' controlling by the robot.

On the other hand, if the focus is on the child behaviour and the technical aspect is of a lower importance, the robot can be controlled by a human rather than an algorithm. This paradigm, where the robot is tele-operated to interact with a naive partner is called Wizard of Oz (WoZ) and is used in numerous studies to explore the psychologic side of HRI Riek (2012).

Deep Learning With the quantity of data logged and the high number of interaction achievable with the free-play sandbox, it supports the type of requirement for recent Machine Learning approaches such as deep learning. The similar position of the children in all interactions makes the combination of data from different interaction easier than other less compact systems.

From the information collected on the children, social behaviours can be extracted and used on a robot.

3 Implementation

The software-side of the free-play sandbox is entirely open-source[1]. It is implemented using two main frameworks: Qt QML[2] for the graphical interface of the game, and the *Robot Operating System* (ROS) for the modular implementation of the data processing and behaviour generation pipelines. The graphical interface interacts with the decisional pipeline over a bidirectional QML-ROS bridge that we have developed for that purpose.

Figure 3 presents the software architecture of the sandbox.

3.1 Interactive game

The interactive game (Fig. 3.1) is coded using QML, and displays a main background image on top of which items (animals, humans and objects) can be moved. The children can also use a drawing mode to create coloured strokes on a layer between the background and the items, which adds another layer of unconstrained interaction to the game (Figure 2). The game exposes the image of the background, the drawings, and the positions of the objects as ROS TF frames.

3.2 Sensing

Two Intel RealSense SR300 RGB-D cameras are mounted at fixed positions on the sandtray frame, with custom designed 3D-printed brackets that ensure that the cameras are oriented towards the children's face. Because the cameras are rigidly mounted onto the sandtray's frame, their accurate geometric transformations with respect to the sandtray screen are known. Combined with hardware calibration, it allows for accurate localisation of the children and in particular, children's faces. In addition to the images, both cameras can perform stereo audio recording. One ROS node per camera (Fig. 3.2) publishes on dedicated topics the audio and video streams.

A third 'external' (and non-calibrated) camera is usually used as well to record the environment of the experiment with a wider angle (*environment camera* in Figure 1).

3.3 Robot Control

As stated in section 2.2, a robot (Fig. 3.9) can act as play partner instead of one of the children. This robot can either be autonomous selecting actions based on the inputs provided by the sensors and the game or be controlled by a human in a Wizard of Oz fashion.

Autonomous The current implementation exposes a large number of information on the game and the state of the child that can be used in the robot controller. The position of every item is exposed as a TF frame, the background is segmented in zones of identical colors (Fig. 3.5), social element of the state the interaction are collected through the RGBD camera and the microphone facing the child. As visible on Figures 1 and 4, the camera covers the head of the child as well as most of the upperbody, and applying libraries such as DLib and OpenPose, the position of facial feature and skeleton of the child are extracted and can be used to obtain: head gaze, gaze and gestures such as pointing. All these inputs can be combined to provide

[1] Source code: `https://github.com/freeplay-sandbox/core`

[2] `http://doc.qt.io/qt-5/qmlapplications.html`

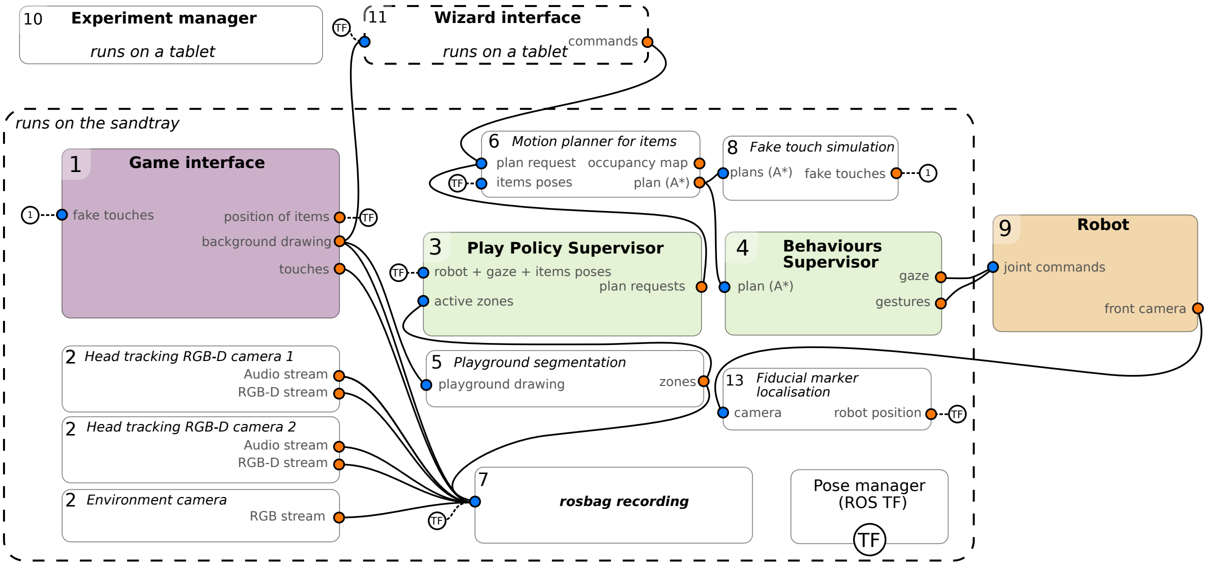

Figure 3: Software architecture of the free-play sandbox. Left (purple) nodes are connected to the sandtray (game interface (1) and camera drivers (2)). Nodes in the centre (green) implement the behaviour of the robot (play policy (3) and robot behaviours (4)). Several helper nodes are available, in particular, segmentation of the children drawings into zones (5), A* motion planning for the robot to move in-game items (6). Nodes are implemented in Python (except for the game interface, developed in QML) and inter-process communication relies on ROS. 6D poses are managed and exchanged via ROS TF.

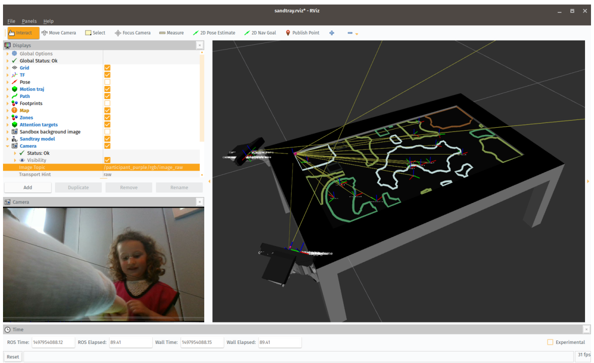

Figure 4: The free-play sandbox, viewed at runtime within ROS RViz. Simple computer vision is used to segment the background drawings into zones (visible on the right panel). The poses and bounding boxes of the interactive items are published as well, and turned into an occupancy map, used to plan the robot's arm motion.

the robot with more social inputs to test the sociability of a robotic controller (Fig. 3.3) and its impact on the interaction.

The robot's location is obtained by displaying fiducial markers on the touchscreen before the start of the interaction, so the transformation between the robot coordinate system and the touchscreen is known (Fig. 3.13). And this robot location can also be used to identify gazes from the child to the robot.

To make the children believe the robot is moving objects on the touchscreen, we synchronise a moving pointing gesture of the robot (Fig. 3.4) and a series of fake touches (Fig. 3.8) appied on the screen, moving the desired object. Once an object and a goal position have been selected, a planner (Fig. 3.6) generate a path for this image using the A* algorithm on an occupancy map obtained with the items footprints, then this plan is sent to a nodes synchronising the actuation on the robot and the fake touches on the game.

Other actions such as gaze, pointing or speech are also exposed as simple ROS topics.

Wizard-of-Oz To allow an experimenter to control the robot, a GUI to control the robot (Fig. 3.11) is provided and presents an identical representation of the state of the game on an other application which can be used on a tablet for example. The wizard can drag the objects in a similar fashion as what the child would do on the Sandtray, and on the release, the robot executes the dragging motion on the Sandtray, moving an object to a new location. The source code can be easily modified to add new specific buttons to execute other actions, such as having the robot talk to the child.

3.4 Experiment Manager

We have developed as well a dedicated, web-based, interface can be used by the experimenter to manage the whole experiment and data acquisition procedure (Fig. 3.10). This interface ensures that all the required software nodes are running, allow the experimenter to check the status and, if needed, to start/stop/restart any of them. It also help managing large data collection campaigns by providing a convenient web interface (usually used by the experimenter on a tablet) to record the demographics, resetting the game interface after each session, and automatically enforcing the acquisition protocol (see Table 1).

This interface has been extensively used to acquire the dataset that we present at Section 5.

4 Canonical procedures for data collection & analysis

The section presents *canonical* procedures to acquire data during testing, to pre-process it, and analyse it. We call them *canonical* because they are standard procedures, and where relevant, well integrated into the software pipeline of the sandbox (e.g., ROS integration) and represent state-of-the-art techniques. For the specific purpose of manually annotating the social interaction, we introduce as well a novel coding scheme, resulting from the synthesis of several existing techniques (Section 4.4 below).

However, these procedure are not normative. Researchers interested in reusing the free-play sandbox task for their own research would naturally adapt and extend these protocols to their own needs. Besides, certain aspects (most notably, the audio processing) are yet to be properly investigated.

Table 1: Data acquisition protocol

Greetings *(about 5 min)*
• explain the purpose of the study: showing robots how children play • briefly present a Nao robot: the robot stands up, gives a short message, and sits down. • place children on cushions • complete demographics on the tablet • remind the children that they can withdraw at anytime
Tutorial *(1-2 min)*
explain how to interact with the game, ensure the children are confident with the manipulation/drawing
Free-play task (up to 40 min)
• initial prompt: *"Just to remind you, you can use the animals or draw. Whatever you like. If you run out of ideas, there's also an ideas box. For example, the first one is a zoo. You could draw a zoo or tell a story. When you get bored or don't want to play anymore, just let me know."* • let children play • once they wish to stop, stop recording
Debriefing *(about 2 min)*
• answer possible questions from the children • give small reward (e.g., stickers) as a thank you

Table 2: List of datastreams typically recorded. Each datastream is timestamped with a synchronised clock to facilitate later analysis.

Domain	**Type**
children	audio
	face (RGB + depth)
robot	full 3D pose
environment	RGB
touchscreen	background drawing (RGB)
	touches
	position and orientation of in-game items
static transforms between touchscreen and facial cameras	
cameras calibration informations	

4.1 Protocol

We typically adhere to the acquisition procedure described in Table 1 with all participants. To ease later identification, each child is also given a different and brightly coloured sports bib to wear.

Importantly, during the *Greetings* stage, we show the robot both moving and speaking (for instance, "Hello, I'm Nao. Today I'll be playing with you. Exciting!" while waving at the children). This is meant to set the children's expectations: they have seen that the robot can speak, move, and even behave in a social way.

Also, the game interface of the free-play sandbox offers a tutorial mode, used to ensure the children know how to manipulate items on a touchscreen and draw. In our experience, this has never been an issue for children.

4.2 Data collection

Table 2 lists the datastreams that are collected during the game. By relying on ROS for the data acquisition (and in particular the `rosbag` tool), we ensure all the $\approx$10 streams are synchronised, timestamped, and, where appropriate, come with calibration information (for the cameras mainly). In our experiments, cameras were configured to stream in qHD resolution (960$\times$540 pixels) in an attempt to balance high enough resolution with tractable file size. It results in *bag* files weighting $\approx$1GB per minute.

In our own experiments, all the data (including up to 5 simultaneous video streams) was recorded on a single computer (quad core i7-3770T, 8GB RAM) equipped with a fast 4TB SSD drive. This computer was also running the game interface on its touch-enabled screen (sandtray), making the whole system compact and easy to deploy (one single device).

4.3 Data processing

Face and body pose analysis Off-line post-processing can be done on the images obtained from the cameras. We rely on the CMU OpenPose library Cao et al. (2017) to extract for both children the upper-body skeleton, 70 facial landmarks including the pupil position, as well as the hands' skeleton (when visible).

Further processing is possible: As the position of the camera, a potential robot and any object on the game is known, this landmarks can be mapped to high level behaviours such as pointing or looking at an object. Additional analysis can be done on the facial landmarks to other social states, such as main emotion felt by the child.

Audio processing Similar processing can be applied on the audio stream. Library such as OpenSMILE provide audio features such as pitch and loudness contour, which inform on the general state of the child.

As of today, no reliable speech recognition engine exists for children Kennedy et al. (2017), but in the future, the audio should provide textual information on the requests and comments produced by the child.

Game interactions analysis Game features are also produced by the different nodes involved in the analysis of the game. The Playground segmentation produce a map of the regions based on the colour which can be used with the positions of the animal to identify from which zone to which zone an animal has been moved. The relative position of animal can also indicate if two animals have been moved closer. These relations and the drawing inform on what high level action the child is doing and can be used to infer the child's goal or desire.

4.4 Annotation of Social interactions

Annotating social interaction beyond surface behaviours is generally difficult. The observable, surface behaviours typically result of a superposition of the complex and non-observable underlying cognitive and emotional states. As such, these deeper socio-cognitive states can only be indirectly observed, and their labelling is typically error prone.

Our aim is to provide insights on the social dynamics, and we have synthesised a new coding scheme for social interactions that reuse and adapt established social scales. Our coding scheme (Figure 5) looks specifically at three axis: the level of *task engagement* (that distinguishes between *focused*, *task oriented* behaviours, and *disengaged* – yet sometimes highly social – behaviours); the level of social engagement (reusing Parten's stages of play, but at the micro-task level); the social attitude (that encode attitudes like *supportive*, *aggressive*, *dominant*, *annoyed*, etc.)

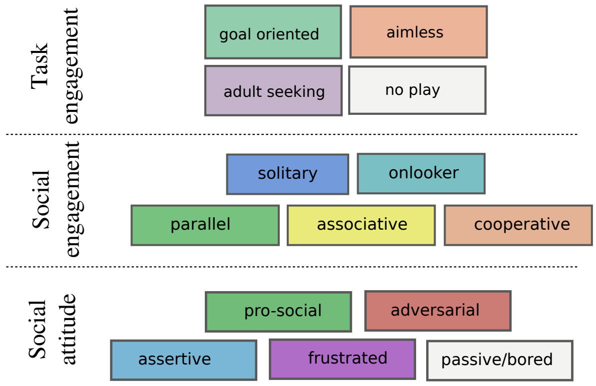

Figure 5: The coding scheme used for annotating social interactions occurring during free-play episodes. Three main axis are studied: task engagement, social engagement and social attitude.

Task engagement The first axis of our coding scheme aims at making a broad distinction between 'on-task' behaviours (even tough the free-play sandbox does not explicitly require the children to perform a specific task, they are still engaged in an underlying task: to play with the game) and 'off-task' behaviours. We call 'on-task' behaviours *goal oriented*: they encompass considered, planned actions (that might be social or not). *Aimless* behaviours (with respect to the task) encompass opposite behaviours: being silly, chatting about unrelated matters, having a good laugh, etc. These *Aimless* behaviours are in fact often highly social, and play an important role in establishing trust and cooperation between the peers. In that sense, they should not be discarded.

Social engagement: Parten's stages of play at micro-level In our scheme, we characterise *Social engagement* by building upon Parten's stages of play. These 5 stages of play are normally used to characterise rather long sequences (at least several minutes) of social interactions. Here, we apply them at the level of each of the micro-sequences of the interactions: one child is drawing and the other is observing is labelled as *solitary play* for the former child, *on-looker* behaviour for the later; the two children discuss what to do next: this sequence is annotated as a *cooperative* behaviour; etc.

By suggesting such a fine-grained coding of social engagement, we enable proper analyses of the internal dynamics of a long sequence of social interaction.

Social attitude The constructs related to the social *attitude* of the children derive from the *Social Communication Coding System* (SCCS) proposed by Olswang et al. Olswang et al. (2006). The SCCS consists in 6 mutually exclusive constructs characterising social communication (*hostile*; *pro-social*; *assertive*; *passive*; *adult seeking*; *irrelevant*) and were specifically created to characterise children communication in a classroom setting.

We transpose these constructs from the communication domain to the general behavioural domain, keeping the *pro-social*, *hostile* (whose scope we broaden in *adversarial*), *assertive* (i.e., dominant), and *passive* constructs. In our scheme, the *adult seeking* and *irrelevant* constructs belong to Task Engagement axis.

Finally, we have added the construct *Frustrated* to describe children who are reluctant or refuse to engage in a specific phase of interaction because of a perceived lack of fairness or attention from their peer, or because they fail at achieving a particular task (like a drawing).

Video coding The coding is performed post-hoc with the help of a dedicated annotation tool (Fig. 6 which is part of the free-play sandbox toolbox. This tool can replay and randomly seek in the three video streams, synchronised with the recorded state of the game (including the drawings as they are created). An interactive timeline displaying the annotations is also displayed.

The annotation tool offers a remote interface for the annotator (made of large buttons, and visually similar to Figure 5) that is typically displayed on a tablet and allow the simultaneous coding of the behaviours of the two children. Usual video coding practices (double-coding of a portion of the dataset and calculation of an inter-judge agreement score) would have to be followed.

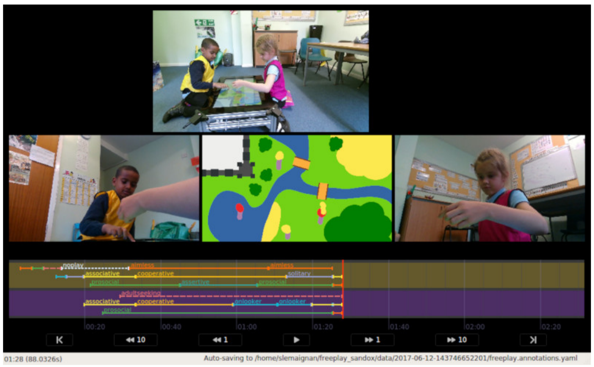

Figure 6: Screenshot of the dedicated tool developed for rapid annotation of the social interactions.

5 Baseline Datasets

We have been using the free-play sandbox task for an initial, large scale, data collection over a period of 3 months during Spring 2017.

This campaign aimed at (1) extensively evaluating the task itself (would children engage and exhibit a large range of social dynamics and behaviours?), (2) making sure the whole software architecture and data acquisition pipeline were reliable (they were), and (3) establishing two experimental baselines for the free-play sandbox task: the 'human' baseline on one hand (child-child condition), an 'asocial' baseline on the other hand (child - *non-social* robot condition). These two baselines are situated at the two ends of the spectrum of social interaction. They aim at characterising the qualitative and quantitative bounds of this social spectrum and can be used by the research community to evaluate given interaction policies.

A detailed description of the dataset is outside of the scope of this paper, and we only provide hereafter cursory informations on the dataset. Specific details regarding the methodology and the acquisition procedure can be found on the dataset website[3]. The dataset is open and accessible to any interested researcher, subject to adequate ethical clearance.

In total, 120 children were recorded for a total duration of 45 hours and 48 minutes of data collection. These 120 children (age 4 to 8) were split into two conditions: a child-child condition and a

[3] `https://freeplay-sandbox.github.io/`

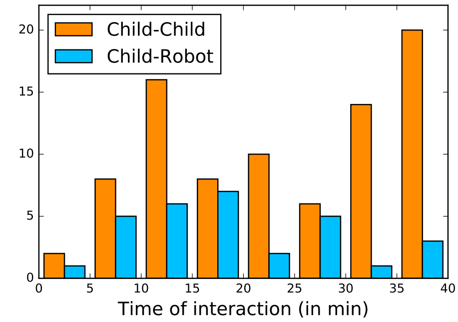

Figure 7: Durations of the interactions for the two conditions.

child-robot condition. In both condition, and after a short tutorial, the children were simply invited to freely play with the sandbox, for as long as they wished (with a cap at 40 min).

In the child-child condition (as seen in Figure 6), 45 free-play interactions (i.e., 90 children) were recorded with a duration M=24.15 min (SD=11.25 min).

In the child-robot condition, 30 children were recorded, M=19.18 min (SD=10 min). In this later condition, the robot behaviour was coded to be purposefully *asocial*: the robot would autonomously play with the game items, but would avoid any social interaction (no social gaze, no verbal interaction, no reaction to the child-initiated game actions).

Over the dataset, the children faces are detected on 98% of the images, which validates the location of the camera and the children to use the cameras to obtain facial social features.

Figure 7 presents an histogram of the durations of the interactions for the two baselines. The distribution of the child-child interaction durations shows that (1) all children engage easily and for non-trivial amounts of time with the task; (2) the task leads to a wide range of level of commitment, which is desirable: it supports the claim that the free-play sandbox is an effective paradigm to observe a range of different social behaviours; (3) long interactions (¿30 min) can result, which is especially desirable to study social dynamics.

In contrast, and notwithstanding the smaller number of participants, the distribution of the child-robot interaction durations shows these interactions are generally shorter. This is expected as the robot was explicitly programmed not to interact with the children, resulting in a rather boring (and at time, awkward) situation where the child and the robot where playing side-by-side – in some case for rather long periods of time – without interacting at all.

6 Discussion & Conclusion

6.1 Analysis of the free-play sandbox

The free play sandbox elicits a *loosely structured* form of play: the actual play situations are not known and might change several times during the interaction; the game actions, even though based on a single interaction modality (the touchscreen), are varied and unlimited (especially when considering the drawings); the social interactions between participants are multi-modal (speech, body postures, gestures, facial expressions, etc.) and unconstrained. This loose structure creates a fecund environment for children to express a range of complex, dynamics, natural social behaviours that are not tied to an overly constructed social situation.

The interaction is loosely structure. It is nonetheless structured: First, the physical bounds of the sandbox (an interactive table) limit the play area to a well defined and relatively small area. As a consequence, children are mostly static (they are sitting in front of the table) and their primary form of physical interaction is based on 2D manipulations on a screen.

Second, the game items themselves (visible in Figure 2) structure the game scenarios. They are iconic characters (animals or children) with strong semantics associated to them (like 'crocodiles like water and eat children'). The game background, with its recognizable zones, also elicit a particular type of games (like building a zoo or pretending we explore the savannah).

These elements of structure (along with other, less important, ones) make it possible for the free-play sandbox paradigm to retain some key properties that makes it a practical and effective scientific tool: because the game builds on simple and universal play mechanics (drawings, pretend play with characters), the paradigm is essentially cross-cultural; because the sandbox is physically bounded and relatively small, it can be easily transported and practically deployed in a range of environments (schools, exhibitions, etc.); because the whole apparatus is well defined and relatively easy to duplicate (it essentially consists in one single touchscreen computer), the free-play sandbox facilitates replication of findings in HRI while preserving ecological validity.

6.2 Towards the machine learning of social interactions?

We presented a set-up and data set of relatively unconstrained interaction between children and between a robot and a child. The set-up captures a rich set of multimodal streams which can be used to mine the social, verbal and non-verbal communication between two parties engaging in a rich free-play interaction. The data holds considerable promise for training social signal interpretation software, such as engagement interpretation or eye gaze reading. The dataset collected has sufficiently rich data and a wide range of multi-modal dimensions making it particularly suitable for Deep Learning of social signal processing algorithms. It also allow for very rich input to action selection mechanisms needed for autonomous robot behaviour. Future work will focus on mining the data for social patterns occurring in play situations, as per Parten's classification, and will attempt to extract social signals relevant to drive the interaction. Some early results show, for instance, that deep learning shows considerable promise for high-resolution tracking of eye gaze from the RGB video streams.

Acknowledgments

This work has been supported by the EU H2020 Marie Sklodowska-Curie Actions project DoRoThy (grant 657227).

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