# Playground Social Interaction Analysis using Bespoke Wearable Sensors for Tracking and Motion Capture


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## ABSTRACT

Unstructured play is considered important for the social, physical and cognitive development of children. Traditional observational research examining play behaviour at playtime (recess) has been hampered by challenges in obtaining reliable data and in processing sufficient quantities of that data to permit credible inferences to be drawn. The emergence of wearable wireless sensor technology makes it possible to study individual differences in childhood social behaviour based on collective movement patterns during playtime. In this work, we introduce a new method to enable simultaneous collection of GNSS/IMU data from a group of children interacting on a playground. We present a detailed description of system development and implementation before going on to explore methods of characterising social groups based on collective movement recording and analysis. A case study was carried out for a class of 7-8 year old children in their school playground during 10 episodes of unstructured play. A further 10 play episodes were monitored in the same space following the introduction of large, loose play materials. This experimental design allowed us to study the effect of an environmental intervention on social movement patterns. Sociometric analysis was conducted for comparison and validation. This successful case study demonstrates that sensor based movement data can be used to explore children's social behaviour during naturalistic play.



## KEYWORDS

Curve Similarity, Social Interactions, Play, Childhood Social Behaviour, Wearable Sensors, Tracking and Motion Capture


## 1. INTRODUCTION

School playgrounds are significant spaces in children's lives but their importance as a context for social, physical and cognitive development is under-researched and poorly understood [8]. In particular, social group structure and dynamics are thought to be significantly related to childhood wellbeing but have rarely been studied in naturalistic play episodes. One reason for this is that observation of children's unstructured social interactions can be challenging to implement, requiring highly resource intensive methods that are difficult scale to the group level (e.g. see [1]).

Developments in wearable wireless sensor technology raise the possibility of capturing important social behaviours 'in the wild' [11], allowing the study of group behaviour in natural contexts. There is an emerging literature concerning the use of such technologies to study individual differences in childhood social behaviour. Veiga and colleagues have used RFID to establish that frequent proximity to other children during play is a good predictor of social competence [9]. In the present study we were motivated include movement data into the study of play as another source of social insights. For example, Moreno and colleagues have demonstrated using simulation, how social roles during games can be inferred from movement data alone [7]. Inspired by these studies, as well as by innovative movement studies of non-human animal social behaviour [10], our guiding research question was, "*how can we use wireless technology to capitalise on the rich potential of playground behaviour as a way to explore and understand childhood social development?*"

In the current paper we introduce a new method to enable simultaneous collection of GNSS/IMU data from a group of children interaction on a playground, on repeated occasions. We present a detailed description of the system development and implementation before going on to use a descriptive case study approach to explore methods of characterising social groups based on the resulting data. We define 3 types of gameplay based on our observations and formulise movement similarity methods to classify social gameplays. Through cluster analysis we firstly validate our results against sociometric data and then compare pre- and post-intervention results in terms of gender gap and social groups.

The specific aims of the study were to 1) construct a user-friendly system of wearable sensors to track children's movements and interactions on the playground, and 2) develop ways to use the resulting sensor data to characterise social play behaviours. These aims are important for the field of psychology, given the potential to reduce costs, and increase replicability of research into social play outside of laboratory conditions.

## 2. METHODS

### 2.1 Ethical considerations

The study was approved by the institutional ethical review board. As participants were minors, informed consent was sought from those with parental responsibility. Permission to participate was given in all but one case.

### 2.2 The Case Study

The project team was interdisciplinary, with team members from Computer Science, Education, Psychology, Psychiatry and Playwork. The team devised a case study approach to the research, with an emphasis on the development of the wearable sensors, the feasibility of using them with children, and qualitatively evaluating whether resulting data would be likely to be useful for the study of play.

Participants were 9 girls and 9 boys all from one year-3 class in an urban, Primary School (age 7-8 years).

The project was introduced to the children during a lesson, and they were invited to ask questions of the researchers. Children were involved in personalising the wearables using pens and fabric paints. The aim of these activities was to raise interest and engagement with the project.

Once the sensors and firmware were developed (see below), the basic idea of the study was to collect data while the children were engaged in free-play on the school playground. We also introduced a basic 'loose parts play' intervention to provide information about how changes to the play environment may influence children's interactions. Loose parts play introduces to the play space loose materials that have an ambiguous affordance [3]; the aim is to foster creativity and collaboration. In the *baseline condition* (10 sessions) children were left to play without any toys or other materials. In the *intervention condition* (10 sessions) loose materials, balls, and access to 2 large fixed play structures were provided and children were facilitated by two adult play workers.

Sensor data were collected over 27 sessions of at least 45 minutes each; of these, 7 initial sessions were assigned as pilot or habituation, 10 sessions as '*baseline*' and 10 sessions as '*intervention*'.

The playground (Figure 1) is 24×35 metres and was divided into zones defining areas of interest (shown in green in Figure 1), inaccessible zones (shown in red and dark red) and boundary zones (shown in blue and orange). During data collection, recordings were made using two cameras that covered the area, for ground truth data collection and validation.

### 2.3 Wearable Sensors and Devices

In order to analyse collective movement patterns of children in the playground and to study their social interactions, sub-metre positioning accuracy and synchronised measurement for each child during the playtime were required. The technology also had to be unobtrusive and not inhibitory to children and their play. To meet such requirements, off-the-shelf equipment were not available. Therefore, two bespoke sensors/devices were designed and developed in-house: (i) a wearable head-mounted sensor with Inertial Measurement Unit (IMU) and Global Navigation Satellite System (GNSS) for precise positioning; and (ii) a wearable shoe-mounted IMU sensor for activity monitoring and motion capture (see Figures 2 and 3).


**Figure 1: The Playground**

#### 2.3.1 GNSS/IMU Sensor

The GNSS/IMU sensor incorporates a raw data GNSS module and active antenna supporting concurrent reception of multiple satellite systems (GPS, GLONASS, BeiDou and Galileo). Raw GNSS data include carrier phase, code pseudorange and Doppler measurements. Logging of raw GNSS data allows off-line processing and cancellation of carrier-phase ambiguity and ionospheric noise using base station data. However, depending on the location of the sensor, obstructions such as playground trees, walls, metal fencing, or nearby buildings interrupted the line-of-sight between the GNSS antenna and the satellites and, as a result, compromised the positioning accuracy. To counter this, concurrent information from multiple satellite systems, and the capture of both raw and real-time position-velocity-time (PVT) GPS data was used to increase redundancy improve the positioning precision. The sensor is also equipped with 9-axis IMU system combining a 3- degree-of-freedom (DoF) accelerometer, 3-DoF gyroscope, and 3-DoF magnetometer. The sensor uses Bluetooth Low Energy (BLE) for wireless connectivity for configuration and data streaming and a micro-SD card is used to log the IMU and GNSS data. Highly accurate satellite time is used to synchronise the sensors. Figure 2 shows the in-house built GNSS/IMU Sensors and antenna.

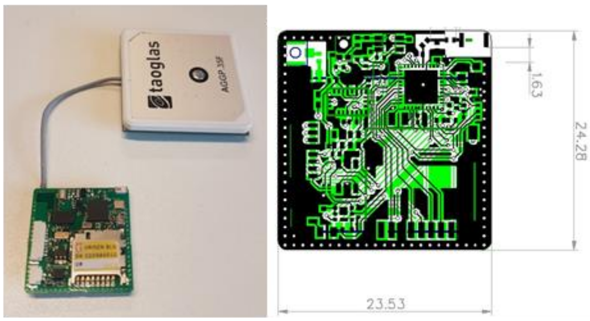


**Figure 2: Bespoke GNSS/IMU Sensors**

Wearable and protective shells for the GNSS/IMU sensors were also designed, 3D modelled and printed. The protective shell allows the sensor, antenna and battery to safely reside beneath the brim of a baseball cap. This provides a flat horizontal space for the GNSS antenna which provides the optimum line-of-sight (LoS) to satellites. Figure 3 shows the 3D printed models of the head-mounted (baseball cap brim) protective shell for the GNSS/IMU sensors.

**Figure 3: 3D printed head-mounted protective shell for the GNSS/IMU Sensors**

#### 2.3.2 Shoe Flap IMU Sensor

Foot-worn sensors can provide step-detection, activity monitoring and movement analysis, and can be used to augment position calculations [12, 13]. In this project, a wearable IMU sensor was designed and developed in-house firstly to improve positioning accuracy and secondly to measure activity levels during playtime. During periods in which there is no clear line-of-sight view of satellites (e.g. when close to the school building or under playground trees), step detection using foot-worn IMU sensors can maintain the positioning accuracy at sub-metre precision levels. The bespoke sensors include 9-axis IMU sensors for 3 DoF motion capture and BLE wireless connectivity for configurations and synchronisation with read time. Figure 4 shows the miniature IMU sensor. Again, the IMU sensor and its battery is placed into a protective shell in shape of a shoe flap that can be worn on top of shoes with or without shoe laces. Figure 5 shows the designed and 3D printed shoe-flap for the IMU sensor.

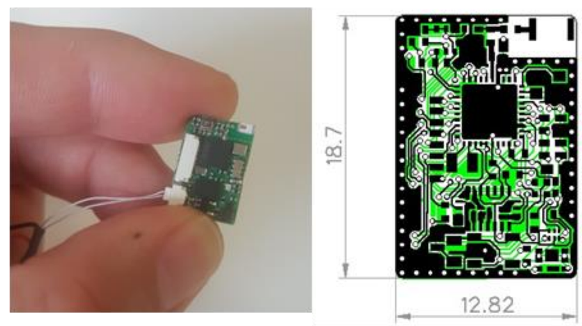


**Figure 4: Bespoke IMU Sensors**

**Figure 5: 3D printed show-flap protective shell for the IMU Sensors**

## 2.4 Sociometric Analysis

The social structure of the class was analysed using a standard sociometric nomination procedure [2]. This was intended to give insight into the basic social organisation of the group. Each child was interviewed on a 1:1 basis in a quiet area of the school and was asked to nominate their 3 most preferred classmates in order of preference. Photographs of all participating classmates were used to support nominations, and children were assured that nominations were confidential. Self-nominations were not permitted.

Group structures were identified based on betweenness centrality, using the Girvan-Newmann algorithm [4] implemented in NetworkX [5]. The class social network based on these nominations is shown in Figure 6. As Figure 6 shows, strong sex segregation is evident in the class network.

The sociometric network was also used to explore the social connectedness of the children by examining the number and strength of nominations each child received. We examined the number of nominations received (in-degree), in-degree weighted by preference ranking ($1^{st}$=3, $2^{nd}$=2, $3^{rd}$=1), and reciprocated nominations (sum of edges between pairs of nodes).

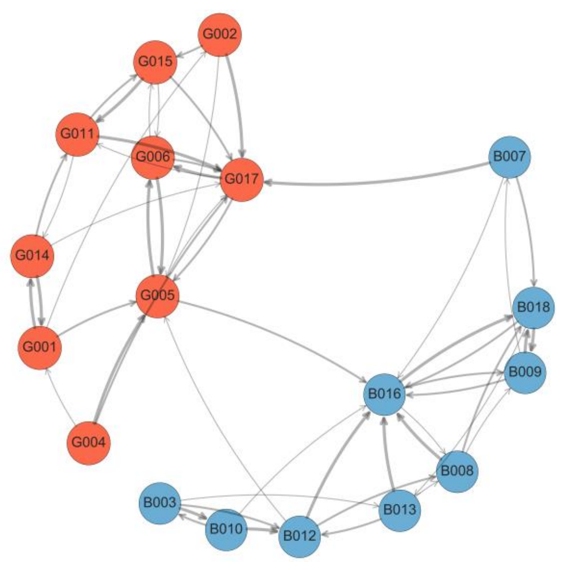


**Figure 6: Sociogram of the class network. Nodes labelled G- and B- represent girls and boys respectively. Nodes with similar colours are communities detected after the 1st iteration of the Girvan-Newmann algorithm.**

## 3. Analyses

Once we had created the bespoke sensors and successfully used them to collect data in the *piloting*, *baseline*, and *intervention* conditions, we addressed our second aim: to develop ways to use the sensor data to characterise social play behaviours. In this section, we report 2 ways in which we approached this aim. Firstly, we discuss the development of spatio-temporal metrics matched to social gameplay type and, secondly, we discuss methods of deriving an affiliation network using measures of movement similarity between players.

## 3.1 Types of Social Play

Based on the video recordings and field observations, we observed and noted three main social play types that our method would need to characterise: (i) Hangout Play, (ii) Pursuit Play and (iii) Focal Play.

### 3.1.1 Hang-out Play

In hangout play, two or more children spend time together close to each other. They may stay in same location or move to different locations, so this form of play is primarily characterised by the duration of colocation, not where that colocation occurs. Hangout play is identified using a metric that involves the warping of point-to-point distances between pairs of individuals over a sliding window of time. Figure 7 shows two traces that represent an example of hangout play, coupled with the point-to-point distances between the individuals.

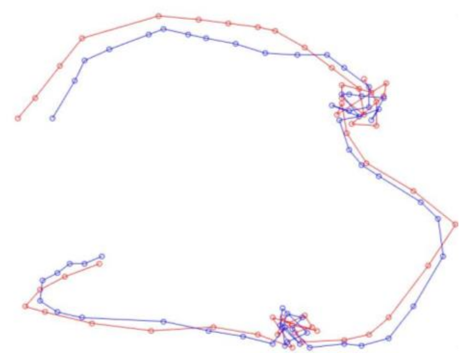

**Figure 7: Hangout Play Example**

### 3.1.2 Pursuit Play

In pursuit play, two or more children follow each other in a chase; whilst they follow similar paths, they need never be collocated. In other words, there is spatial similarity with variable temporal lag. Figure 8 shows an example of pursuit play.

### 3.1.3 Focal Play

In focal play, two or more children visit the same location at different times. Examples include children bringing materials from different places to a shared location in pursuit of some common goal such as creating a structure. Other examples include ball games like basketball or football in which children follow the ball and return to the goal area at different times. Due to their unsynchronised returns to the focal point, point-to-point distances do not represent the associations in this game type (shown in Figure 9). Similarly, curve-matching based on asynchronous warping of area or distance is not representative of the associations in focal play.

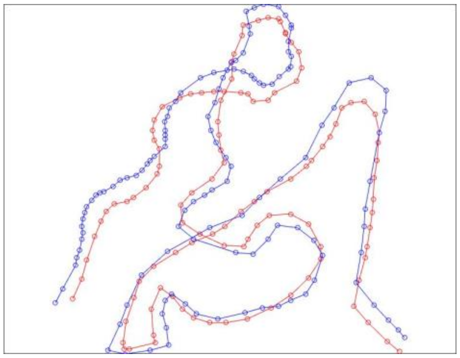

**Figure 8: Pursuit Play Example**

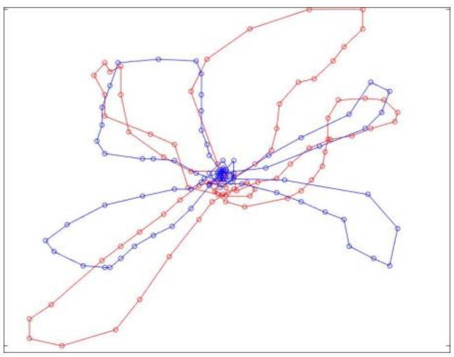

**Figure 9: Focal Play Example**

## 3.2 Curve Similarity Matching for Gameplay Movement

In this section, we propose and formulise different spatio-temporal metrics to measure the associations between children engaged in each type of play.

### 3.2.1 Definitions

Here, curves A and B are considered polygonal chains where $A = [0, m] \to \mathbb{R}^2$ for $i = \{0, \dots, m-1\}$ and $|A| = m$ and $B = [0, n] \to \mathbb{R}^2$ and for $i = \{0, \dots, n-1\}$ and $|B| = n$. $A_i$ (and $B_i$) denotes the segment between i$^{\text{th}}$ and (i+1)$^{\text{th}}$ points. $\psi_{A_i}$ denotes the azimuth angle of segment $A_i$. $(x_i, y_i)$ are polygon points of $A_i$ in local Cartesian coordinates converted from longitude and latitude points from GNSS results.

### 3.2.2 Warping Turning Distance

The curve trajectories of children in the playground are deducted as polygon chains synchronised by GNSS accurate real time. Conventional curve matching methods e.g. Arkin et al [8] using Warping Turning Distance (WTD) defined as

$$WTD(A, B) = \min_{\substack{\theta \in \mathbb{R} \\ u \in [0,1]}} \left[ \int_0^1 (\psi_A(s) - \psi_B(s+u) + \theta)^2 ds \right]^{\frac{1}{2}} \quad (1)$$

where $\theta$ is the optimal azimuth angle (orientation) and $u$ is the optimal starting point for best match between the two polygons. While such methods are useful for shape similarity and classification they may not represent the gameplay types we need to quantify in this work.

### 3.2.3 Warping Euclidean Distance

Similarly, we considered Warping Euclidean Distance (WED) [8], which can be defined for spatial curve matching defined as

$$WED(A, B) = \min_{u \in [0,1]} \left[ \int_0^1 \left(x_1(s) - x_2(s+u)\right)^2 + \left(y_1(s) - y_2(s+u)\right)^2 ds \right]^{\frac{1}{2}} \quad (2)$$

However, this method is not useful in the case of pursuit play. In pursuit play, two children follow each other with a time delay and may not be collocated at any time. The time lag between them can adversely influence the WED metric.

### 3.2.4 Warping Fréchet Distance

We considered using the Fréchet distance as a basis for adding links in the play network. In Fréchet distance, the pair of contributing points sweeps continuously on each curve considering the flow and the ordering of the curve points [6, 7]. Since the rate of travel for either point may be non-uniform, Warping Fréchet Distance (WFD) is a more suitable method for curve similarity in ordered (synchronised) polygon chains in our case study. The Fréchet metric is defined as infimum of

$$WFD(A, B) = \inf_{\alpha, \beta} \max_{u \in [0,1]} \left[ \mathcal{D}\left(A(\alpha(u)), B(\beta(u))\right) \right] \quad (3)$$

where $\alpha(u)$ and $\beta(u)$ range over continuous and increasing functions with $\alpha(0) = 0$, $\alpha(1) = m$, $\beta(0) = 0$ and $\beta(1) = n$ only. $\mathcal{D}$ is the Euclidean distance between the sweeping points.

Figure 10 shows examples of WED and WFD for Pursuit Play showing the efficiency of WFD over WED in gameplay similarity measurement.

Table 1 shows the potential usefulness of the methods described above for gameplay type defined in section 3. The comparison is based on manually-defined example data shown in Figures 7, 8 and 9.

**Table 1: Comparison of Distance Metrics vs Gameplay Types**

| | Game Play | | | |
|---|---|---|---|---|
| Distance Metric | Hangout | Pursuit | Focal | Random |
| WTD (rad) | 2.461 | 1.543 | 3.981 | 14.322 |
| WED (m) | 1.086 | 2.699 | 5.001 | 13.511 |
| WFD (m) | 0.629 | 1.239 | 1.140 | 2.246 |

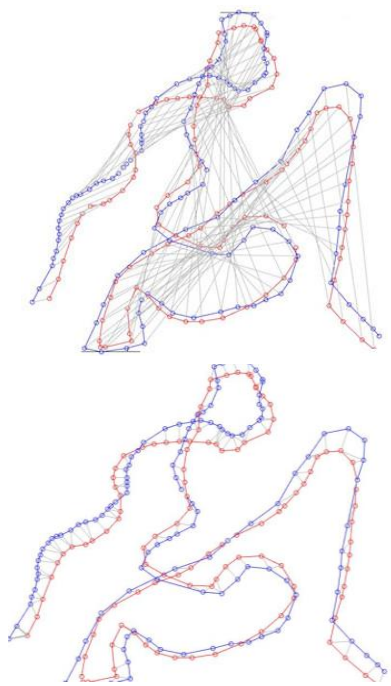

**Figure 10: Warping Euclidean Distance (top) compared to Fréchet Distance Metric (bottom) in Pursuit Play**

## 3.3. Creating a Movement-based Social Affiliation Network

Considering the WFD method as likely to be the most informative irrespective of play type, the second piece of analysis involved creating a social affiliation network summarising spatio-temporal data from each child across the 10 *baseline* and 10 *intervention* episodes, and using similarity between pairs of children to add links between nodes as described in 3.3.1.

### 3.3.1 Gameplay Similarity Decision Problem

Let $\mathbb{G}$ be the set of continuous sliding windows $S_j^t$ of t seconds of movement data subsets (polygon chains) over the course of playground playtime sessions:

$$\mathbb{G} = \{S_j^t | j = 1..p, A_j = f(S_j^t)\} \tag{4}$$

For each two children and on each $S_j^t$ we define the following decision problem:

Given two gameplays and a threshold ε ≥ 0 decide whether

$$F_\varepsilon = \{(s,t) \in [0,m] \times [0,n] | WFD(A^s, B^t) \leq \varepsilon\} \tag{5}$$

$F_\varepsilon$ describes all pairs of sliding windows $S_j^t$ and their corresponding polygon chains $A_j$ whose distance is at most $\varepsilon$. For $r$ children in the class we calculate the Overall Affiliation Matrix (OAM) which is a symmetric $r \times r$ matrix $\mathcal{W}$ where the weights $\mathcal{W}_{i,j}$ are

$$\mathcal{W}_{i,j} = |F_\varepsilon^{\mathrm{i,j}}| \tag{6}$$

## 4. Results

The OAM was used to calculate the affiliation networks graph based on averages over the *baseline* and *intervention* episodes. We also represent these data as dendrograms and clustergrams as this allows for visualisation of hierarchical clusters (sub-group formations) in the class group. We present these results descriptively before discussion of their possible interpretation with respect to our research aims in section 5.

Figure 11 and 12 show the class networks for *baseline* and *intervention*.

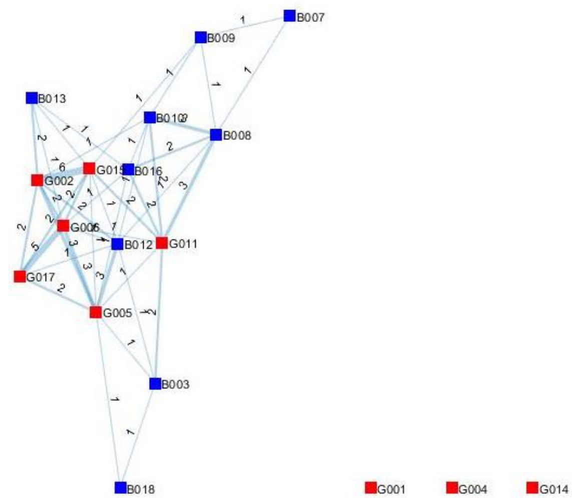


**Figure 11: Network Graph *Baseline***

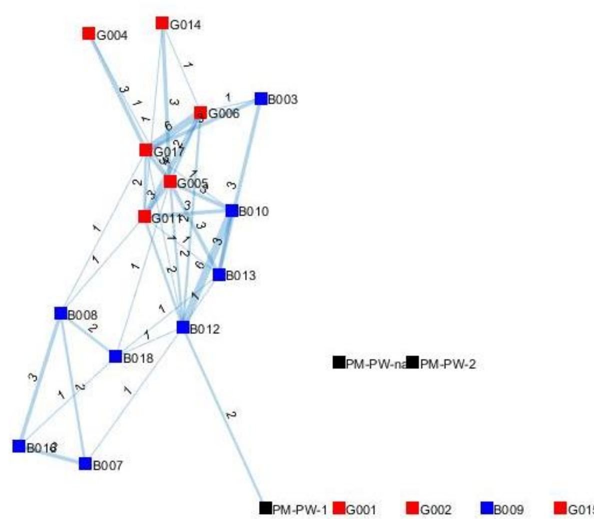


**Figure 12: Network Graph *Intervention***

These network graphs show the overall affiliation matrices at the least permissive threshold for establishing a link. A 'spring' layout is used for the visualisation, meaning nodes placed closer together have stronger connections. Nodes appear isolated from the main graph when they were not sufficiently similar to any other child to add a link to the OAM as described in 3.3.1 above.

To clarify the information contained in the networks, we also present the information as clustergrams. Figure 13 and 14 show the class clustergrams for *baseline* and *intervention*. The playworker data have also been included for the *intervention* matrix.

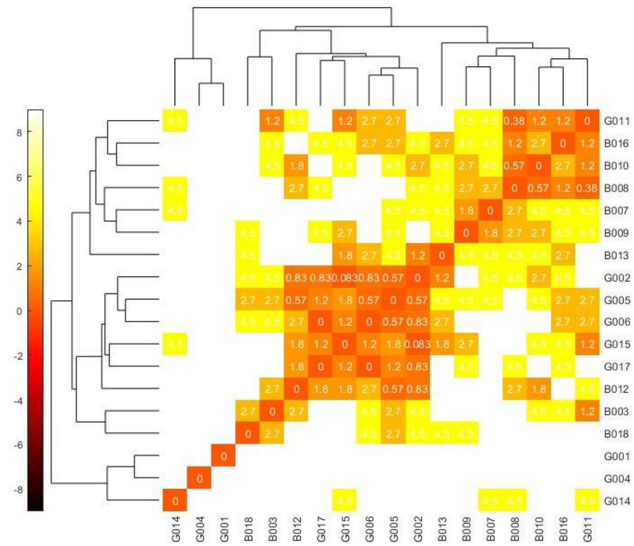


**Figure 13: Clustergram *baseline* data. B=Boy, G=Girl**

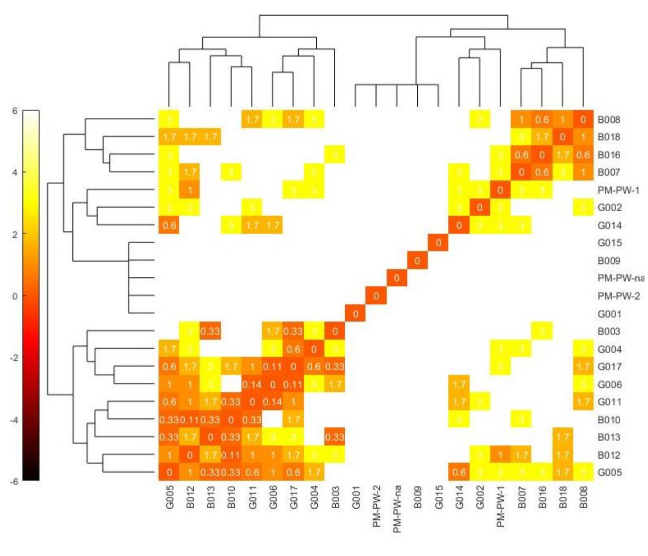


**Figure 14: Clustergram *intervention* data. B=Boy, G=Girl, PM-PW=Playworker**

The hierarchical structures of the group are shown in the dendrogram at the top of the diagram (repeated also on LH side). The coloured squares represent the strength of association in the OAM between each pair of participants as described in 3.3.1 (White/yellow are the 'weakest' connections, darker orange the 'stronger' ones).

## 5. Case Study Analysis and Discussion

In this case study we have demonstrated the development and successful implementation of a bespoke sensor for tracking children's movements during episodes of unstructured social play. Importantly, the method appears to be ethically acceptable to children and families. Indeed, discussions with the participating school showed us that they were more comfortable with the GNSS/IMU methods of data capture than with video, as child data could more readily be anonymised using sensors.

The method we developed did not prove inhibitory to social play behaviours and children quickly habituated to the wearables. Children enjoyed participating in the assembly and decoration of the wearable caps and this turned out to be a good strategy for engaging the children in the research. The case study therefore illustrates that we met our objective to construct a user-friendly system of wearable sensors to track children's movements and interactions on the playground.

Our second objective was to develop ways to use the resulting sensor data to characterise social play behaviours. This is an important consideration when deciding whether or not it would be worth developing the method beyond this initial case study. The identification of three social movement patterns of interest in this paper (section 3.1) provides a useful reference point for future research.

The Overall Affiliation Matrices (visualised as clustergrams and networks in section 4), show there is interesting social information contained in the trajectories of children in a playspace. For example, in the *baseline* condition network there is evidence of sex segregation, something we also observed in the nomination network (see section 2.4). At the first level we observe one main cluster composed mainly of boys with one girl included, and a second (larger) cluster composed mainly of girls with one boy included. A third set of weakly connected girls is also observed. It is interesting to note that node G-004 is an isolated node in the *baseline* network (Fig. 13), as this child is also isolated in the sociometric network (i.e. she received no incoming nominations in the directed graph, see Fig. 6).

In the *intervention* network it is encouraging to see that the playworkers are represented by isolated or very weakly connected nodes, as their role was intended to be as 'hands-off' as possible from the children's play. As in the *baseline* condition (Fig. 13), child G-001 is poorly connected, as are children B-009, G-015 and G-002.

Interestingly, in the upper right-hand corner of the clustergram, we see a more sharply defined single-sex cluster of boys in the *intervention* data. Matching this to our fieldnotes we see that this corresponds to what we have named '*the football effect*.' When the play materials were available to the children, a small group of boys chose to engage in this activity in preference to all others. The second cluster at the first level of the *intervention* data is also of interest in that here we see more integration between the sexes, four boys clustered alongside five girls. In this condition we see the previously isolated child G004 is included in the cluster. Informal observations based on fieldnotes suggest that this increased integration occurs during collaborative interactions with the loose parts materials.

From this exploratory case study, it is clear that using curve similarity to define links in an affiliation network is a potentially useful tool for exploring social structures and dynamics as they occur during naturalistic play. This could help to test hypotheses in developmental social psychology that have previously been impractical to explore, especially those that apply to whole group behaviour. For example, the hypothesised influence of play type and activity levels on the emergence of sex segregated behaviour in pre-pubescent groups could be studied [14], or theories of distinct social-behavioural phenotypes associated with different neurodevelopmental conditions could be tested [15]. The method also has potential as an objective test of change in social behaviour following intervention.

## 6. Conclusions

In this work we created and successfully implemented a new method of studying children's social group behaviour at playtime using movement and positioning data. Bespoke wearable sensors for motion capture, high-accuracy localisation and game play analysis have been designed and developed. Empirical data using a class of 18 children were collected in 27 sessions of sessions. Three main types of playground game play were identified using video data and fieldnotes. We have proposed and compared different observation metrics to define similarity between children during these different types of playground social play. Sociometric analyses were also conducted and used for comparison and validation.

Experimental results were demonstrated using affiliation network graphs and clustergrams. Sex segregation in both sociometric and in sensor derived network results were observed. This gives a certain face-validity to the methodology as sex segregation in play behaviour is a well-documented phenomenon [6]. However, both '*the football effect*' and the more integrated group seen in the *intervention* condition, indicate possible environmental effects on sex segregation during play. It is important to reiterate that, at this stage in the development of our methodology, we did not aim formally to test specific hypotheses. Rather we aimed to explore whether we could conclude that our method is suitable for capturing differences in social behaviour as it occurs during different play environments. The results from this case study suggest the method does have promise in this direction.

The next steps include (i) examining associations between traditional measures of social ability or social status and those derived from the properties of the OAM interaction network; (ii) investigating activity levels & group formation processes; (iii) developing machine learning classifiers for different play types, validated against video.

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