Sensing Interpersonal Synchrony between Actors and Autistic Children in Theatre Using Wrist-worn Accelerometers

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ABSTRACT

We introduce a method of using wrist-worn accelerometers to measure non-verbal social coordination within a group that includes autistic children. Our goal was to record and chart the children's social engagement – measured using interpersonal movement synchrony – as they took part in a theatrical workshop that was speci cally designed to enhance their social skills. Interpersonal synchrony, an important factor of social engagement that is known to be impaired in autism, is calculated using a cross-wavelet similarity comparison between participants' movement data. We evaluate the feasibility of the approach over 3 live performances, each lasting 2 hours, using 6 actors and a total of 10 autistic children. We show that by visualising each child's engagement over the course of a performance, it is possible to highlight subtle moments of social coordination that might otherwise be lost when reviewing video footage alone. This is important because it points the way to a new method for people who work with autistic children to be able to monitor the development of those in their care, and to adapt their therapeutic activities accordingly.

ACM Classi cation Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords

wearable sensing; accelerometers; theatre; autism; interpersonal synchrony; cross wavelet

INTRODUCTION

Autism, or autism spectrum condition (ASC), refers to a range of developmental conditions that are characterised by dif - culties with social interaction. People with ASC can struggle with non-verbal communication, including the use of gaze, imitation, and other social cues. These dif culties might arise during infancy, when ASC children are slower to grasp social signals, and fail to imitate or copy the movements of others in the same way that neurotypical children do [3]. This creates a barrier to both learning and social engagement.

An important measure of a person's social engagement is the degree to which they move in synchrony with others. Interpersonal synchrony – the non-random temporal coordination of two or more people [5] – is found to be less prevalent in ASC than in neurotypicals. Motion-capture technology was used to show this by measuring movement coordination (or lack of) between interactants [8]. Yet most studies of this kind are lab-based, and primarily focus on dyads rather than groups.

There are of course instances when even those with severe autism are able to engage and interact socially. Indeed many adults with ASC develop mechanisms to help them navigate social situations. It follows that moments of improved interpersonal synchrony do occur in ASC, however eetingly. Capturing these moments might allow us to pinpoint instances of social engagement, both from the point of view of understanding the mechanisms at play, and as a way of charting an individual's development.

Wearable sensing provides an opportunity to take research on interpersonal synchrony and autism out of the lab and into "the wild". Body-worn accelerometers can be used to track ASC children – and everyone they typically interact with – as they go about their everyday life. The ecological richness of such data comes at a cost to privacy.

We propose an alternative approach: using wearables to study

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their parents and carers. Yet we do not know exactly why these games work, or what the neural and psychological mechanisms at play are. As a rst investigation of this, we use wearable sensing to record the movements of actors and ASC children during a Flute performance, and use the data to chart their interpersonal synchrony.

In this paper we present an approach to collecting physical movement data in the challenging environment of a live theatrical performance involving autistic children. We describe a novel application of cross-wavelet analysis for exploring the interpersonal synchrony of up to 10 participants. We then demonstrate how this information can be used as a measure of social engagement to aid researchers studying autism, both as a way of charting a child's development, and as a mechanism for automatically annotating videos of long-term interaction.

Related Work

Interpersonal synchrony measures the dynamics of interaction between people rather than the speci c nature of their behaviours. It is more concerned with the temporal coordination and shared rhythm between interactants, rather than how they mirror, or imitate, one another [5]. It was originally studied by developmental psychologists, with early work attempting to quantify bodily synchrony by looking at stills of a movie [4]. Thanks to advances in sensing technology, interpersonal synchrony has become a topic of research in elds such as machine learning, robotics, and human-centered computing [5]. When people move together in synchrony, they tend to have greater rapport with one another [16]. Synchrony has been shown to be an important component in enhancing the success of joint goals [23]. And it has also been shown to effect af liation in human-robot interactions [13].

In ASD, correlations were found between the ability to synchronise movement with others and sentence production [8]. The same work showed that ASD children are both less able to synchronise socially with others, and that their manner of movement when imitating is different. In another study autistic children who were sat on rocking chairs next to their caregivers were found to be less likely to rock in-phase than neurotypical children [20].

Wearables are a promising tool for researching interpersonal synchrony. The accelerometers built into Google Glass, for example, were used to measure dyadic synchrony during conversation [17]. And [24] used wrist-worn sensors (the same E4 devices used in the current work) to demonstrate how large groups of people moving in sync can enhance group af liation.

There is also much potential for wearable applications that support and diagnose people with autism [6]. Google Glass has been explored as a tool to help ASC children with facial expression recognition [26]. Machine learning methods have been applied to wearable sensor data to automatically recognise stereotypical stimming behaviour in autistic participants [2, 28]. Similarly, accelerometer-based features were used to classify aggressive and self-harming behaviours in autism [18]. The focus of our current work, however, is not to automatically recognise speci c behaviours, but rather to try and uncover instances of interpersonal synchrony that might be hidden behind those behaviours.

Figure 1. Interacting with children, and actor-only performance.

Earlier work measured coordinations in dyadic body move-

Figure 2. (Left) data from 6 actors and 4 children over ~2h Saturday performance. Synchronisation gestures highlighted. (Right) E4 watch.

THE INTERACTION MATRIX

With a single variable representing each person's wrist, we evaluate the similarity in movement between different combinations of pairings using CC and ACW. The process of calculating CC and ACW is highlighted for 30s of data in Figure 3. Acceleration data from two participants (adult B and child k4) is compared to generate a cross-wavelet transform in the time-frequency domain. This is averaged across frequencies (y-axis of Figure 3ii) to give an indication of similarity at any ed INTERW9.96is

Figure 3-any

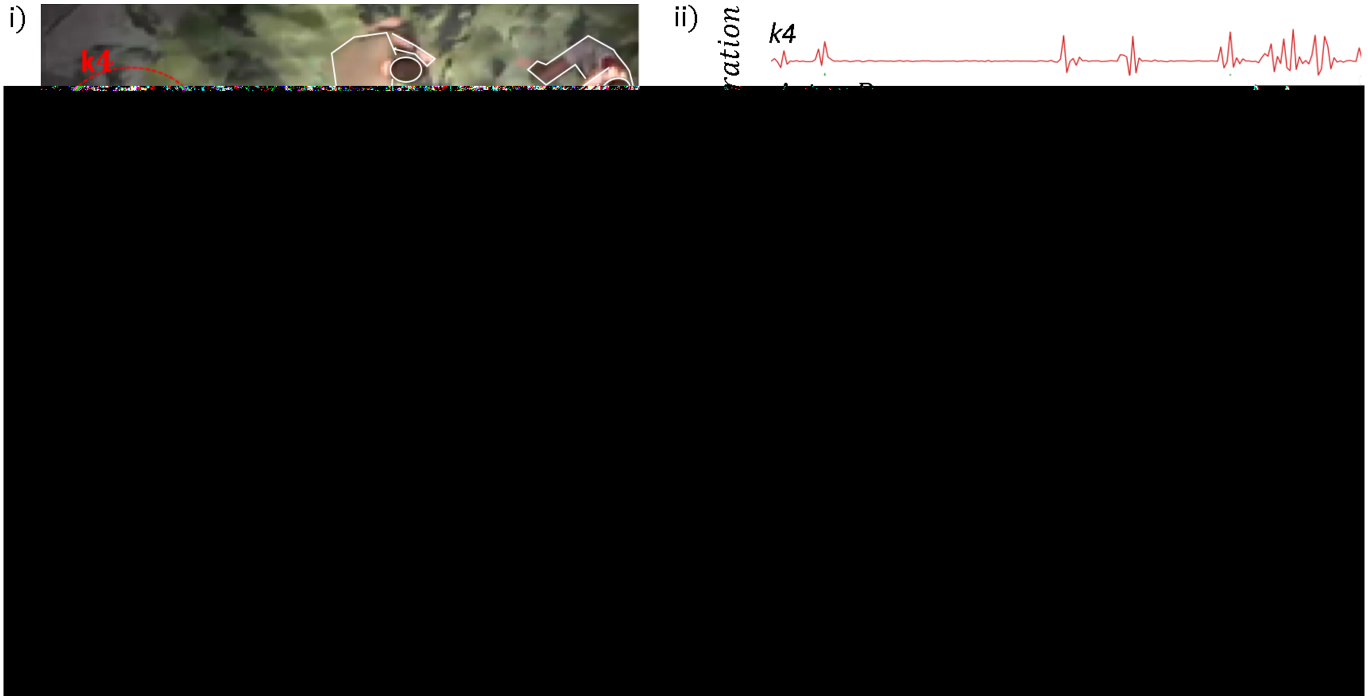

Figure 3. (i) Five actors perform while children (and actor F) watch. (ii) Acceleration from actor B and child k4 over 30s. (iii) Cross-wavelet spectrogram of this data. (iv) Average cross wavelet power (ACW), plotted alongside cross-correlation (CC, calculated using 5s sliding window). (v) Interaction matrices for CC and ACW over 30s period. Note similarity in movement frequencies, but not in temporal correlation, between B and 4.

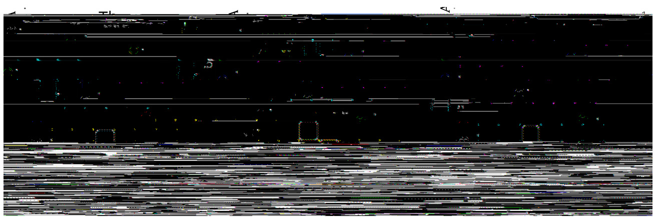

Figure 4. ACW interactions over 2h performances. Dotted squares show main actor-child pairings.

The engagement plot reveals much about the dynamics of this sequence. At time (a), for example, child 3 and A work together to play Titania. Actor D takes over as Bottom, and tries to get child 2 to join – but she is not interested, as shown by the low engagement values (lighter colouring) for that child in (a

Figure 5. Engagement over 2 minute sequence: actors C (as Bottom) and F (as Titania) demonstrate the Doyoyoying sequence; ***a***) actor A and child 3 then work as Titania, with D trying to coax child 3 to play Bottom, ***b***) both children fully commit to their roles, ***c***) B then helps child 1 take on the role of Titania (who manages a single Doyoyoying). (Center) ACW interaction matrix for the 2 minute scene. (Right) view from middle of the scene (***b*** to ***c***).

Figure 6. i) Engagement sequence of participants (Saturday). Dark areas indicate strong synchrony with at least one other person. ii) Maximum engagement for actors vs. children, and their difference. iii) Classifier decision (actors-only vs. interaction) compared to ground truth. Dotted area shows correct detection of an actors-only scene.

	Precision	Recall	AUC
Thursday	.72	.64	.80
Friday	.62	.65	.79
Saturday	.73	.67	.84

Table 1. Event spotting results

(proportion of returned frames which are correct) and recall (proportion of ground truth frames correctly detected). We also show area-under ROC curve (AUC), a threshold-independent measure of performance where 1 is perfect, 0.5 is random [7].

An AUC range of .79 to .84 indicates that a simple threshold-based classifier on engagement groupings can be sufficient to pick-out meaningful events from a long dataset.

DISCUSSION

Sensing in Practice

In a multi-person interaction like this, ideally everyone should be wearing sensors. Unfortunately, consent to record sensor

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