Towards a Full Spectrum Diagnosis of Autistic Behaviours using Human Robot Interactions

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ABSTRACT

Autism Spectrum Disorder (ASD) is conceptualised by the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) [1] as a spectrum, and diagnosis involves scoring behaviours in terms of a severity scale. Whilst the application of automated systems and socially interactive robots to ASD diagnosis would increase objectivity and standardisation, most of the existing systems classify behaviours in a binary fashion (ASD vs. non-ASD). To be useful in interventions, and to overcome ethical concerns regarding overly simplified diagnostic measures, a robot therefore needs to be able to classify target behaviours along a continuum, rather than in discrete groups. Here we discuss an approach toward this goal which has the potential to identify the full spectrum of observable ASD traits.

1 INTRODUCTION

Autism Spectrum Disorder (ASD) is defined by the DMS-V in terms of two behavioural domains: social communication and interaction, and restricted or repetitive behaviours and interests [1]. Recent advances in our understanding have led to the re-conceptualisation of ASD as a spectrum. This concept refers to: (1) differences in presentation and severity within the clinical population, (2) the continuous distribution of "autistic traits" between the general and clinical populations, and (3) subgroups [6]. Diagnosis of ASD cannot, therefore, be thought of as a binary classification (e.g. non-ASD vs. ASD) but rather in terms of severity scales applied to multiple behaviours and traits. Diagnosis thus relies largely on subjective interpretations of various sources of information [2, 10], and children with ASD demonstrate high levels of clinical heterogeneity [4, 11]. The diagnostic standard of ASD could, therefore, be improved by more quantitative, objective measures of social response.

These benefits can be provided by introducing automated systems into the diagnostic process in the form of socially interactive robots [3], and systems to aid in the diagnosis of several behavioural and psychological disorders including ASD [7, 12] have been developed. However, in contrast with the diagnostic requirements, these systems usually approach behaviour classification in a binary fashion; individuals are classed as either *ASD* or *non-ASD* [12]. This lack of sensitivity to intermediate cases brings with it the ethical issues of overly simplified diagnostic measures, such as potentially classifying a large proportion of the behaviours which fall on the autism spectrum as non-ASD [7]. Here, we discuss an approach toward, and the benefits of, non-binary, automated classification of autistic behaviours embedded within human-robot interactions.

2 ROBOTS AS DIAGNOSTIC TOOLS FOR ASD

The prospect of introducing robots into interventions for ASD has become increasingly popular due to findings indicating that robots can promote motivation, engagement, and the occurrence of otherwise rare social behaviours in children with ASD [2, 14]. They have therefore been proposed as an effective tool for helping children develop and employ social skills, and to transfer these skills to interactions with humans [2, 13]. Whilst less attention has been given to the role of robots in ASD diagnosis [14], such an application of robot technology does offer unique benefits including: (1) standardisation of stimulus and recording methodology, and (2) increased repeatability [2, 8]. It has also been argued that a robot's ability to generate social prompts allows for the controlled elicitation and examination of social responses [2]. This is in-line with the goal of diagnostic instruments such as the Autism Diagnostic Observation Schedule (ADOS) [5], i.e. to elicit spontaneous behaviours in a standardised context. Furthermore, the finding that children with ASD interact more with technology than with humans [8] indicates that having a child interact with a robot during assessment may facilitate the production of a wider range of behaviours. This facilitation could, in turn, provide richer data for the purposes of diagnostic analysis [14].

On-line behaviour adaptation is important for autonomous robots in ASD interventions due to the high variability seen between children with ASD [3]. This process requires the system to track and classify the child's behaviour before appropriate responses can be selected. However, many systems which are used to classify behaviours in therapeutic settings are limited to simple, easily distinguished classes; they do not identify intermediate classes [12]. Wall and colleagues [12] used a subset (8 out of 29) of behaviours coded from ADOS to design a diagnostic algorithm which could differentiate between children with and without ASD. Whilst the algorithm could classify cases correctly, Wall and colleagues simplified the problem by removing the middle diagnostic classes, leaving only ASD and non-ASD. As a result, individuals who fall in the middle of the ASD spectrum were identified as non-ASD. Furthermore, an attempt to replicate these findings found that the algorithm was not robust enough to deal with a different dataset and a larger group of coded behaviours was required to identify individuals diagnosed as being in a mid-spectrum ASD class [7].

The spectrum nature of ASD means that to avoid under-identification and to allow the system to provide useful information for decisions about therapeutic approaches, classes of behaviour which do not fall at the extremes of the spectrum, e.g. High-Functioning Autism, should be identifiable. Contemporary approaches to non-binary classification are rare. Bone and colleagues [7] used a similar machine learning method to that of [12], but incorporated all the behaviour codes from ADOS which made the classification system more robust and more accurate. Including the middle diagnostic classes did decrease the accuracy but it still remained high (i.e. 96% dropped to 82%). However, this approach is still labor intensive and time-consuming, and is designed to be run off-line using data collected by the clinician.

3 CLASSIFYING CONTINUOUS BEHAVIOURS USING CONCEPTORS

For a classification system to accurately identify the intermediate classes of ASD, it must be able to classify behavioural patterns ranging from "typical of the general population" to "severely atypical". This can be achieved using purely machine learning methods. However, this requires a large, representative data-set which is often difficult and time-consuming to obtain due to the need to annotate the training data-sets. We therefore require a methodology that can deal with the spectrum nature of ASD by representing behaviours over continuous dimensions, and which requires less data for learning than traditional machine learning methods. One approach is to use conceptors [9]; neuro-computational mechanisms that can be used for learning a large number of dynamical patterns. Conceptors can also be combined and morphed to generate new patterns based on learned prototypical extremes along a behavioural continuum, e.g. a system given the prototypes for "walking" and "running" can generate patterns for "jogging" [9]. This approach assumes that there is a continuum underlying the behaviour, which is well suited to the symptomology of ASD [1], as demonstrated by ADOS [5] which scores behaviours such as speech abnormalities on a scale of 0 ("no evidence of abnormality") to 3 ("markedly abnormal").

To represent the spectrum nature of ASD using conceptors, a recurrent neural network can be provided, for example, with the prototype patterns for typical and markedly abnormal speech behaviour. Relevant information from these input patterns are then represented as the internal state of the system. These internal states are then used for classification, rather than the inputs themselves. Conceptors can be computed to represent the state of each dimension of speech (volume, intonation, stress, etc.) within each pattern, and clustered to form groups. These groups represent the key components of the behavioural continuum which are described by the prototype patterns provided. Morphing of these patterns using linear mixes of the prototype conceptors allows the system to interpolate less extreme patterns into the representational continuum for the behaviour. When provided with inputs of behaviours which fall in the middle of this continuum, the system already has a representation of the internal state this input would provoke, and can classify that input according to the continuum, rather than into a discrete class.

4 DISCUSSION AND CONCLUSIONS

In this paper we have briefly discussed how conceptors could provide an alternative to machine learning methods of automated behaviour classification for ASD diagnosis. By representing behaviours as continuous, the proposed approach has the potential to identify a more complete spectrum of ASD behaviours, rather than just extreme behaviours. Implementing such a system within a socially interactive robot would also leverage those benefits, providing a control system able to more accurately assess child behaviour to inform response selection, as the robot would be able to appropriately select and perform social prompts to elicit behaviours from the child in a standardised and repeatable manner. This application accommodates the goals of diagnostic models, e.g. ADOS [5]. Our next steps are to develop such a system, based on data from the DREAM project [1] [13], to train the system and test its performance.

ACKNOWLEDGMENTS

This work is part of the EU FP7 project DREAM project (www.dream2020.eu), funded by the European Commission (grant no. 611391)

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[1] http://www.dream2020.eu/