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Computational Methods to Support Prototyping of an Adaptive Robot Joystick Controller for Children with Upper Limb Impairments

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***Abstract*— Between 2% to 5% of children are affected by Developmental Coordination Disorders in Canada and have been diagnosed with upper limb impairments, which affect their daily lives and reduces their autonomy. Motor impairments can be part of progressive disorders, so despite regular therapy, progress remains fleeting. Affected individuals therefore consistently face many barriers, including entertainment opportunities, as availability of off-the-shelf inclusive technology is very limited. Our long-term goal is to develop a play-mediator robot, which would facilitate play between children with motor impairments and their peers or family members. Here, games that the robot can play are remotely controlled by the participants, using appropriate interfaces (e.g. joysticks). In this paper, we take the first step towards that goal and develop an adaptive joystick controller that can compensate for individual deficits. We monitor movement statistics to determine if re-calibration of the controller is necessary. Moreover, we propose a computational model of data 'distortion', as a tool for developers to test their technology in the very early stages of prototype development, without requiring access to participants. This work is validated with data from healthy adults and children with upper limb impairments.**

I. Introduction

Between 2% to 5% of children are affected by Developmental Coordination Disorders in Canada and have been diagnosed with upper limb impairments, which affect their daily lives and reduces their autonomy. Examples of those conditions include Cerebral Palsy (CP) which has been diagnosed in between 1 and 4 per 1,000 live births across the world [1], Spinal muscular atrophy [1] which concerns 1 in every 6,000 to 10,000 children. Moreover, approximately 1 per 4000–6000 children are born with chromosome deletion, and one in 40,000-100,000 children are born with ataxia-telangiectasia [2]. The common factor of all those conditions is motor impairments, including motor control difficulties and fine motor skills challenges, amongst others. These difficulties impair daily tasks and can severely alter the quality of life of people affected. Most of those individuals rely on joysticks to perform some tasks, such as controlling a power-wheelchair. However, upper limb impairment can impact the way the user gives commands, due to e.g. high movement variability, drift, asymmetric force. Power wheelchairs already include compensation mechanisms where the user's characteristics are hard-coded [3], however, they need to be regularly manually re-calibrated to take progress or regression of a child's motor control abilities into account [2]. Those systems are often quite expensive and, to the best of our knowledge, there is currently no affordable off-the-shelf solution available for this demographic. Outside of utilitarian tasks, joysticks are also often used in a leisure context, e.g. for video games. Unfortunately, there exists no adaptive joystick solution in this context and users must rely on joysticks which are available on the market and often not suitable for their demographics. Common issues with the currently available joysticks include graspability, or the joystick being too sensitive for such variable movements. The lack of joysticks for our target demographics is therefore creating significant barriers to enjoyment and play, especially for children, for whom play is also crucially important for their social, emotional, cognitive and motor development.

This work is part of a bigger over-arching project that aims at developing a play-mediator robot, that would allow children with disabilities to play with their peers through controlling the robot [4]. The goal of this work is, therefore, to bridge that gap and develop an adaptive joystick controller that can compensate for individual motor impairments, such as drift, force asymmetry and movement variability, but also continuously adapts over time to support the user's skills. To support this work, we also developed a computational model of upper limb impairments, which is grounded in the literature of motion kinematics and analysis, and, as a first step, has been validated on data of children with upper limb impairments controlling a simulated robot. In this paper, we propose a system architecture and implementation details for our controller.

II. Related Work

Play is paramount for child development and has an important role in the context of therapy, as it facilitates adherence, motivation and engagement. While there are many great examples of robots being used in a game context for therapy [4], the literature is more scarce when it comes to upper limb impairments. Indeed, a very limited number of studies use "social" robots and fully exploit their functionalities and appeal. In a study aimed at increasing arm mobility, the children could trigger a reaction from the CosmoBot

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[1]https://rarediseases.org/rare-diseases/spinal-muscular-atrophy/

[2]https://rarediseases.org/rare-diseases/ataxia-telangiectasia/

[3]https://www.albertahealthservices.ca/assets/hospitals/grh/grh-programs-and-services-i-can-centre-resources-maximizing-use-of-standard-power-wheelchair-joystick.pdf

[4]Note, we are using the terms 'disability' or 'impairments' according to the Accessibility for Ontarians with Disabilities Act (AODA), [3]

robot when the required gesture was performed correctly [5]. Another pilot study employed small graspable mobile robots in a Pacman-like game [6]. The Nao robot was also able to increase motivation and involvement in exercises of children with CP when carrying out repetitive training [7]. The robot provided feedback and adapted the exercises based on performance. The Ursus robot lead to increased collaborative behaviours from children and was also able to adapt exercises to each participant, while monitoring and learning from the interaction [8]. Finally, Tasevski et al. reported increased non-verbal communication, gestures and verbal production with a custom-designed robot meant to address the motivation issues children face [9].

In our work, we focus on children with upper limb impairments and specifically on, but not restricted to, cerebral palsy. We are trying to understand movement production better and how their impairments might affect joystick usage. First, there is a great degree of individual variation in motor development and abilities, mirroring the large variety of motor and cognitive impairments for each individual and the different levels of severity of the condition [10]. We also studied work on movement and kinematics analysis, in order to identify movement characteristics. In general, in CP, slowness of movement and muscular weakness are common [11], as well as a lack of appropriate force control which leads to undershooting or overshooting the movement target [12], [13]. Movement variability is typically higher, with lower signal-to-noise ratio and higher jerk [14]. Finally, drifts are often present, with a higher proximal movement drift being linked with increased muscle weakness and a distal drift evidencing an increased muscle weakness and tone [15]. Moreover, while accurately controlled reaching usually appears between 5 and 13 months of age and is typically improved until 9 years of age [16], [17], [18], children with CP do not follow the same timeline and consistently show deficits in reaching and grasping behaviours [19], [20], [11], [21].

There have been a few attempts to develop an adaptive joystick, using a LSTM network that corrects user input [22]. This approach handled polar coordinates and used a calibration procedure to get training data where the participants had to perform a circular motion with the joystick. Our approach also employs a LSTM network but our training data is created from data of healthy participants, to which we apply distortions, thus obtaining a more general network. Calibration is then used to fine-tune the network to be specific for the person.

III. Distortion Model

First and foremost, developing a robust and accurate distortion model is paramount for the development of adaptive controllers, since this population is hard to reach and recruit for studies, and extra ethical considerations need to be made in order to avoid to waste any child's time when engaging them in an experiment, exposing them to an early prototype. A theoretical model would therefore enable developers to more easily test their prototype on simulated data before recruiting the children. Note, 'distortion' is defined in this paper as a computational method to convert data from healthy participants into (simulated) data of children with upper limb challenges.

A. Data Collection

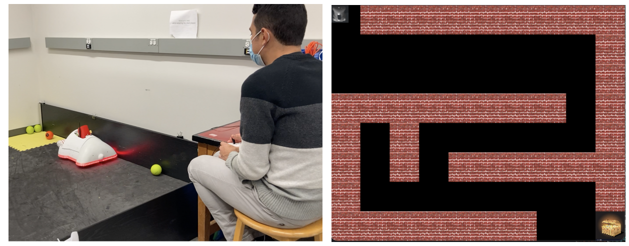

Fig. 1. Left: Two healthy participants interacting with the MyJay robot. Right: maze game for the children data collection

To develop and validate the model, we collected data from 18 healthy adult participants (we refer to this data in the following as 'healthy data') and from 5 children with upper limb impairments (we refer to this data in the following as 'impaired data', in lack of a better term) (See Fig. 1). Both data collections were approved by the University of Waterloo Human Research Ethics Board. The healthy adult participants teleoperated the mobile robot MyJay [23] for 10 minutes. The analysis of this data is described in [24]. Due to Covid-related restrictions we could not run a study where the children teleoperated the physical robot. However, it was feasible to run a study where the children teleoperated a simulated robot through a maze in a computer game with 5 levels of increasing difficulty. Children were recruited from an outpatient rehabilitation center in Ontario, Canada. Five children between 4 and 17 years old took part in the study. Our first participant had type I Spinal muscular atrophy, which is a genetic neuromuscular disease that causes muscles to become weak and atrophied. Affected patients lose a specific type of nerve cell (motor neurons) in the spinal cord that control muscle movement. The second participant had chromosome deletion, which can affect many parts of the body, including weak muscle tone (hypotonia), mild to severe intellectual disability; delayed development of motor skills, such as sitting and walking; and behavioral problems. The next two participants had CP. CP is the most common movement disorder in children. The term CP describes a group of motor impairments and is associated with lesions in areas of the brain that manage movement control, balance and posture. CP occurs when that part of the brain does not develop as it should congenitally (antepartum), or when it is damaged during birth (intrapartum) or post-natally (postpartum). Finally, our last participant was diagnosed with ataxia-telangiectasia, which is a rare inherited condition that affects the nervous system, the immune system and other body systems. It is characterized by: ataxia (lack of coordination) due to a defect in the cerebellum, oculomotor apraxia, Choreoathetosis (abnormal movements such as involuntary jerky movements of the arms, legs and face along with slow, writhing movements of the hands, feet and other body parts), etc.

B. Statistical analysis

To analyze and compare the two populations, we computed different features over non-overlapping windows of 10s, such as the amplitude (difference between the maximum and minimum values), dispersion, frequency of commands and participant drift. We defined the dispersion value as the number of commands outside the expected command range ($x < 0.1$ & $y < 0.1$) divided by the total number of commands. The dispersion can vary between joystick quadrants (see Fig. 2 for an example). A drift reveals a deviation from the intended movement on any joystick axis. We compute four histograms, one for each joystick axis. The drift is identified by looking at the majority bin of the angular histogram centred around each joystick axis (0, $\pi/2$, $3\pi/2$, π). The drift can be different for each joystick direction, e.g. high drift for forward motion, low drift for backward motion. Finally, the force modifiers are defined as the value of the 80th percentile for each axis. The signal-to-noise ratio is calculated as the ratio of the first component to the sum of the remaining components

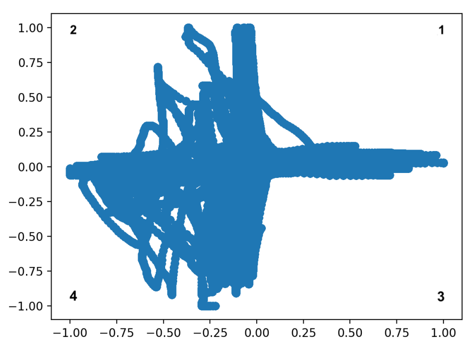

Fig. 2. Example of the joystick profile for one of the children with upper limb impairments. The x axis shows the left/right command of the joystick; The y axis shows the forward/backward command of the joystick. One can notice that the dispersion varies between quadrants, e.g. the lower left quadrant (quadrant 3) has much higher dispersion than the lower right (quadrant 4). The number on the plot indicate the ID of the quadrant.

We performed a Mann-Whitney statistical test to compare both populations. We consider p-values below 0.05 as significant. The analysis revealed that the amplitude of the joystick movements is significantly lower (p-value ≤ 0.001) on each of the four axis for the children with upper limb impairments, compared to the healthy adults. The results on dispersion are more heterogeneous. There is a significant difference for quadrants 2 and 4 (dispersion actually higher for healthy adults), but not for quadrants 1 and 3 (dispersion higher for children) (See Fig. 2 for the quadrants' numbering).

The frequency of commands is also significantly higher (p-value ≤ 0.0001) for the children, compared to the adults. The signal to noise ratio is significantly higher for the children, as well ($p \leq 0.001$ and $p \leq 0.05$). Regarding the drift, it is significantly higher (p-value ≤ 0.0001) for the children in the first 3 quadrants compared to the adults. Drift is however similar in the 4th quadrant.

C. Model

Now that we have representative statistics for each population (See Fig. 4), we can attempt to modify the commands of the healthy adults, so that they match statistics of the children and could "represent" data from individuals with disabilities.

Our distortion model acts on several important signal characteristics: drift (or goal-deviation), and force modifiers to account for under/overshooting and dispersion. Since data from children with upper limb impairments show increased variability, compared to data from healthy participants, it is necessary to include that variability in our model. The force modifiers are therefore not constant over time, but belong to a Gaussian distribution, centred on the target average force modifier with the target standard deviation as the spread.

$$x_{dis} = cmd_x * gauss(f_{\{r,l\}}, std_{\{r,l\}}) \quad (1)$$

$$y_{dis} = cmd_y * gauss(f_{\{f,b\}}, std_{\{f,b\}}) \quad (2)$$

with $f_{r,l}$ the force modifier for the left (right respectively) axis, $f_{f,b}$ the force modifier for the forward (backward respectively) axis. Similarly, std_x is the standard deviation for the given joystick axis.

To achieve the desired dispersion, we calculate how many points need to be modified and the appropriate number of data points are randomly selected and moved in or out of the dispersion area, as required (See Fig. 5).

Finally, to modify the drift, the Cartesian coordinates are converted to polar coordinates:

$$r = x^2 + y^2; \theta = tan^{-1}\left(\frac{y}{x}\right) \quad (3)$$

For each joystick direction, we define:

$$\theta_{dis} = gauss(drift_t, dis_t) \quad (4)$$

With $gauss(C, s)$ a random number in a Gaussian distribution centred around C with spread s. The polar coordinates are then converted to Cartesian coordinates again.

Figure 3 represents an example of data distortion.

D. Experimental Validation

To validate the distortion model, we trained a neural network to discriminate healthy adults and children with disabilities. The network employed is a LeNet classifier [25]: a 2D convolutional layer with 20 filters of size (5x5) with ReLu activation, followed by 2D max pooling with pooling size and stride of size 2x2; a 2D convolutional layer with 50 filters of size (5x5) with ReLu activation, followed by 2D max pooling. The flattened output then goes through a fully connected layer with 500 neurons and ReLu activation and a fully connected layer with 5 neurons and softmax activation. The input of the network is a heat map of the joystick commands, thus creating 64x64 images using non-overlapping windows of 200 data points ($\approx 10s$). The neural network was trained with a learning rate of 0.001 for 5 epochs. It achieved a F1-score of 1.0.

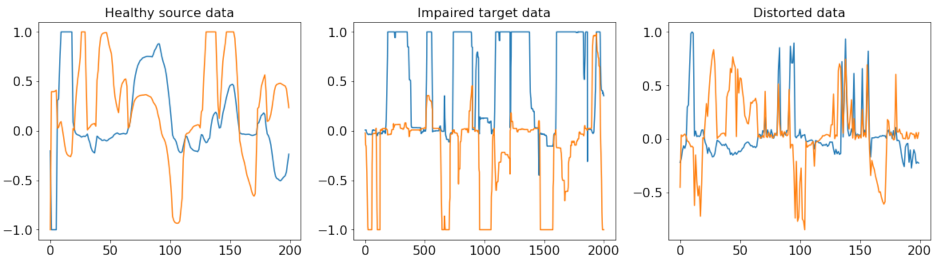

Fig. 3. Example of data distortion. Left: data from a healthy individual, Middle: target data of an individual with upper limb impairments. Right: distorted data. In blue: the x-axis of the joystick, in orange: the y-axis of the joystick

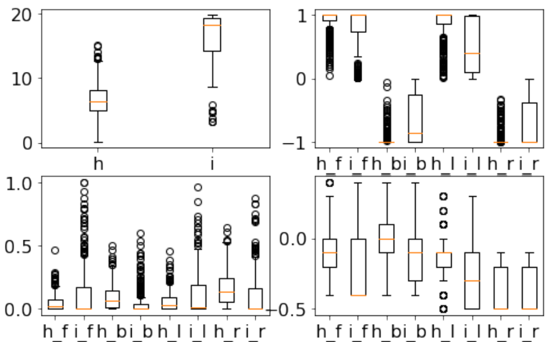

Fig. 4. Top Left: Amplitude. Top Right: Dispersion. Bottom Left: Frequency. Bottom Right: Drift. h_x on the x axis correspond to healthy data, i_x on the x axis correspond to impaired data

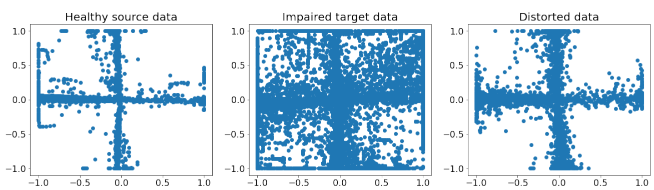

Fig. 5. Example of joystick profile for one of the healthy adults and its modified version after increasing the dispersion.

Once we have a network capable of discriminating both populations, we can develop the distortion model. For each *"source"* data from a healthy adult we apply transformations from the model to try and match each *"target"* data from a child with upper limb impairments. We thus obtain $18 \times 5 = 90$ distorted data sequences. If the model is successful, then the distorted features should be similar to the ones of the target signal, but significantly different from the ones of the source signal. Classifying this distorted data with the neural network yielded a F1-score of 0.18. This is expected, as we apply a global transformation to the data of one person, but we then classify windows of 10s, which overlooks the finer granularity of the game-play. However, applying the modification directly to windows of $10s$ of healthy data, yields a F1-score of 0.97, once again confirming that intra-individual variability is a paramount aspect to take into account. Moreover, statistical tests confirm that the distortion model creates appropriate data. We ran a Mann-Whitney test to compare the distorted data with the healthy data and with the impaired data (See Fig. 8 and 6). There was no significant difference between the amplitude and drift of the distorted data and the *target* data. There was no significant difference between the dispersion of the distorted data and the *target* data for the first and second quadrants. The difference was, however, significant for the third and fourth quadrants. However, there was a statistical difference between the amplitude, dispersion and drift of the distorted data and the *source* data for every joystick axis, thus validating the distortion.

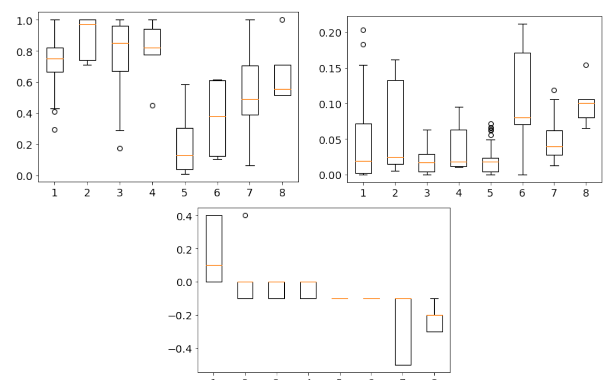

Fig. 6. Comparison between 'distorted' and 'impaired' data for amplitude, distortion and drift. On the x-axis, $\{1, 3, 5, 7\}$ relate to the forward, backward, left, right component of the joystick for the distorted data and $\{2, 4, 6, 8\}$ relate to the forward, backward, left, right component of the joystick for the 'impaired data'.

IV. Adaptive Controller

Since we can now generate satisfactory 'impaired data' from data of healthy participants, we can generate pairs of healthy-impaired data and train a model to correct the distortion.

A. Neural Network for Distortion Compensation

For distortion compensation, we to used a simple regression network made of a Gated Recurrent Unit (GRU) with 16 neurons, followed by 3 fully connected layers: the first layer has 16 neurons and ReLu activation, followed by dropout of 0.1, the following layer has 4 neurons with ReLu activation and the last layer has 2 neurons, and linear activation. The network is trained using a mean-squared error loss and a learning rate of 0.05 for 500 epochs.

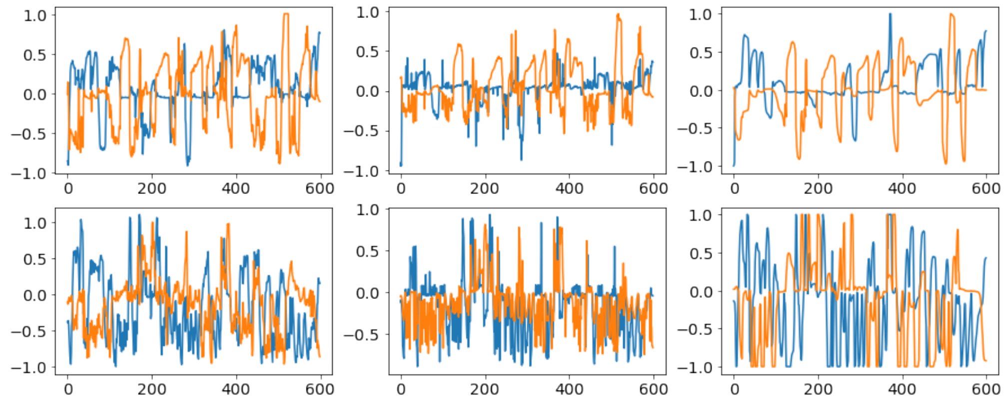

Fig. 7. Example of data correction. Left: healthy source data, Middle: impaired target data. Right: corrected data

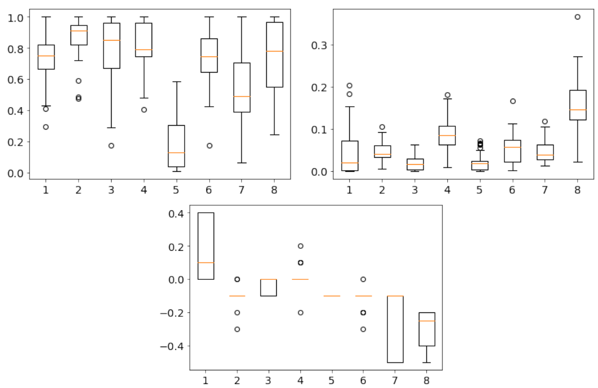

Fig. 8. Comparison between distorted and healthy data for amplitude, distortion and drift. On the x-axis, {1, 3, 5, 7} relate to the forward, backward, left, right component of the joystick for the distorted data and {2, 4, 6, 8} relate to the forward, backward, left, right component of the joystick for the healthy data.

To train our network, the inputs are sequences of a hundred pairs of (x,y) commands distorted using our distortion model and the output is the same pair before distortion. We also tried to train the network on the polar coordinates but the Cartesian coordinates yielded better results. See Fig. 7 for an example of data correction. The correction is not perfect, which is understandable since it was trained on data that went through many different modifiers. It would be unreasonable to expect such a network to be able to deal with such a variety of cases. It is, however, visible that the network is already able to correct force modifiers and reduce noise.

To formally validate that the regression network is suitably correcting the data from impaired individuals, we classify its output, i.e. the corrected data, using our previously trained classifier. The neural network classifier recognizes the corrected commands as healthy data with 99% recall and F1-score of .99, thus validating the regression correction model.

B. Calibration

Our system also comprises a calibration step. The calibration procedure entailed participants separately moving the joystick forward, backward, left and right once. This data was collected before the children started playing the maze game. We did not collect calibration data from healthy adults, as we did not intend on correcting their joystick actions. First, we ensure that the calibration data is representative of the child's. To do so, we compare calibration features and game-play statistics (See Fig. 10).

This comparison reveals that acquiring the calibration data this way does not always yield representative data. First, due to the high movement variability that the children exhibited, learning in one-shot will not give satisfactory results. We would probably need to collect calibration data of the same movements being performed over and over again. Second, children were asked to move the joystick in each direction once, so they were more focused on performing that movement correctly.

Next, we attempted to use the calibration data to fine-tune the correction mode. The performed actions are projected to the x or y axis, as relevant, thus creating new data to fine-tune the neural network, so that it becomes more specific and personalized to the user. Before fine-tuning, we froze the first two layers of the model, i.e the GRU layers and the first fully connected layer. Then we re-trained the network for 50 epochs using a learning rate of 0.0001.

This approach was successful for participants 0 and 1, as the network became more specific to those participants but failed for the other participants. The specificity of the network was tested by applying the correction model to the data of all the children and classifying the output. It appears that when the correction network becomes personalized, it compensate better for that particular participant than for the other participants. Although this approach seems promising, we will need to rethink the calibration procedure to better capture individual characteristics, as well as variability.

C. Continual learning

Finally, the last component in our system concerns continual learning, as capabilities of individuals with upper limb impairments often vary over time: they can improve with therapy, or worsen as most conditions are degenerative. Our approach consists in training a classifier that can classify individual features successfully. A variation of user joystick

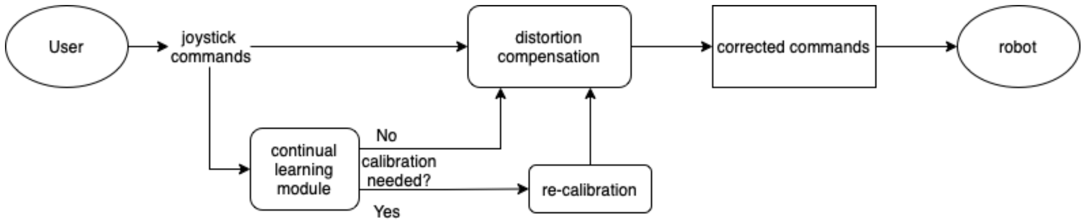

Fig. 9. Our proposed system for the adaptive controller

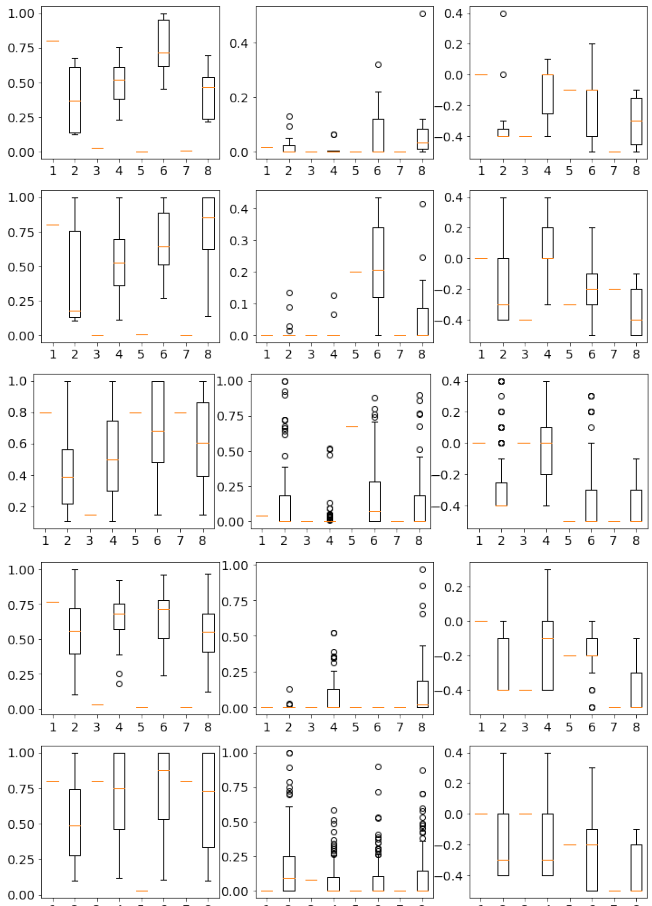

Fig. 10. Example of Calibration data. The first column displays amplitude, the second dispersion and the third one drift. On the x-axis, $\{1, 3, 5, 7\}$ relate to the forward, backward, left, right component of the joystick for the calibration data and $\{2, 4, 6, 8\}$ relate to the forward, backward, left, right component of the joystick for the game data.

behavior should lead to mis-classification, which, in turns, should trigger re-calibration of the system. To test and illustrate this, we trained a classifier to discriminate the different participants, using 200 data points windows. It achieved 0.99 F1-score. Next, we slightly modify the signal by applying a force modifier or drift and check if this data is still correctly classified. Empirical testing shows that slight variations of force, drift or dispersion do not strongly affect classification. Combined variations, however, significantly degrade classification to a score below 60%. This should, of course be validated with data collected over time for different individuals.

V. Discussion and Conclusion

A. System Overview

In this paper we proposed a comprehensive system to design an adaptive joystick controller (see Fig. 9), including a distortion model and a correction model, which we validated on experimental data. We strongly believe that the development of such a distortion model could be an invaluable tool for developers aiming to help children with upper limb impairments, as it will allow them to test their program on simulated data, experimental data being scarce. The system also comprises a calibration step, to personalize the system to the user, as well as a continual learning module that detects if re-calibration is necessary.

The main limitation of this work is the limited amount of data collected for our target population, namely children with upper limb impairments. Unfortunately, this population was very hard to recruit, as the outpatient rehabilitation center still had a lot of precautionary measures in place due to Covid-19 to protect children who are more vulnerable. Moreover, we will need to rethink the calibration procedure to better capture individual characteristics, as well as variability.

Future steps for this project involve validating the system with a physical robot and hopefully recruit children for experimental validation. One important aspect we wish to verify is whether this type of adaptive controller is effective for the children but also especially, if it is desired, accepted and usable. Indeed, over-correction could be experienced by the user as detrimental, as it might impact on the user's learning and their motivation to improve. Our work aims at supporting children, but not over-assisting them, so that they can still feel in control of the game.

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