Robot Simulation of Sensory Integration Dysfunction in Autism with Dynamic Neural Fields Model

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Abstract. This paper applies dynamic neural fields model [1,23,7] to multimodal interaction of sensory cues obtained from a mobile robot, and shows the impact of different temporal aspects of the integration to the precision of movements. We speculate that temporally uncoordinated sensory integration might be a reason for the poor motor skills of patients with autism. Accordingly, we make a simulation of orientation behavior and suggest that the results can be generalized for grasping and other movements that are performed in three dimensional space. Our experiments show that impact of temporal aspects of sensory integration on the precision of movement are concordant with behavioral studies of sensory integration dysfunction and of autism. Our simulation and the robot experiment may suggest ideas for understanding and training the motor skills of patients with sensory integration dysfunction, and autistic patients in particular, and are aimed to help design of games for behavioral training of autistic children.

1 Introduction

Movement disturbance symptoms in individuals with autism have not been considered as an important symptom for a long time. During the last decade, Leary and Hill [17] have offered a radical perspective on this subject. After thorough analysis of the bibliography on movement impairments in autism they argue that motor disorder symptoms may have a significant impact on the core characteristics of autism.

Imprecise grasping, or other motor or executive dysfunctions, observed by autistic patients are caused by a disturbance in a dynamic mechanism that involves multisensory processing and integration. Therefore we investigate how the dynamic aspects of integration of multisensory input influences forming of coherent percept, planning, and coordination of action.

Temporal multisensory integration has previously been discussed in the context of autism in [4,13], in attempts to revile and simulate the underlying biological mechanism of interaction in [10,11] and in the robotics setting in [2,25], and implicitly in many other robotics studies.

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Proper modeling of the temporal integration mechanism requires a dynamic neural model. The main stream connectionist methods, like self-organizing or supervised feed-forward networks and Hopfield type recurrent networks produce static outputs, because their internal dynamics lacks feedback loops and their input space is static. Therefore they are suitable for modeling static behaviors. We are interested in a neural system that can spontaneously exhibit several dynamic behaviors, derived by the interaction between changing input and complex inner dynamics. However, for the sake of controllability and computational expense, we choose the model with least complexity needed. Schoner and colleagues [23,25,8] have adapted the dynamic neural field model of Amari [1] for controlling mobile robots and robot-manipulators. It produces smooth behavioral trajectories satisfying more than one external variable. In this model the attractor is a fixed point, but continuous attractor is approximated in sequential steps. The system goes from one attractor to the other through input-dependent variations. More complex dynamic models that have continuous attractors may suffer high computational expense.

This paper is organized as follows. Section 2 discusses the method for sensory integration used, the experiment design, and the results of a computer simulation. In Section 3, the results of robot simulation are shown. Discussion is offered in Section 4. Last, but not least, we acknowledge the people who have contributed to this work.

2 Temporal Multisensory Integration

2.1 Dynamic Neural Field Model for Multisensory Integration

The dynamic neural fields (DNF) model has been proposed as a simplified mathematical model for neural processing [1,7]. The main characteristics of this model are its inherent properties for stimulus enhancement, cooperative, and competitive interactions within and across stimuli-response representations.

Recently Erlhagen and Schoener [8] formalized the extension of the theoretical model to dynamic field theory of motor programming, explaining the way it was and could be used for robotics and behavioral modeling applications. Before and since, DNF model has been used in robotics for navigation and manipulation of objects [9,25,14], for multimodal integration [22] and imitation [21]. Applications feature biologically convincing methods that can optimize more than one behavioral goal, contradicting sensory information, or sensory-motor task that requires common representation. For instance, Iossifidis and Steinhage [14] applied the dynamic neural fields to control the end-effector's position of a redundant robot arm. Two problems were solved by this implementation: smooth end-effector trajectory is generated and obstacles are avoided. Faubel and Schoener [9] use dynamic neural fields to represent the low-level features of the object such as color, shape, and size. The fast object recognition achieved is beneficial for an interaction with a human user. Thelen et al. [26] have modeled the dynamics of the movement planning by integrating the visual input and motor memory to generate the decision for the direction of reaching.

The mathematical description of the DNF model incorporates the formation of patterns of excitation, their interaction, and their response to input stimuli. The basic equation of one dimensional homogeneous field of lateral-inhibition can be represented in the following way:

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int w(x-y) f[u(y)] dt + h + s(x,t) \tag{1}$$

where

- τ is the time constant for dynamics of a neuron
- x and y is the located positions of neurons
- u is the average membrane potential of neurons located a position x at time t
- h is the resting potential
- s(x,t) is the input stimulation level at position x at time t.

An interesting for us feature of the model is that it possesses dynamical properties useful for multisensory and sensory-motor integration. We suggest that the dynamical characteristics of the model can be exploited for investigating the temporal aspects of multimodal integration. The temporal window for integration is shown to have an impact on the multisensory interaction, so we investigate the possibilities for its adaptation within the neural field model and its impact on the computational outcomes. The presentation of the sensory cues within the DNF model is in the form of Gaussian distributions. We tune the variance of these distributions according to the experimental findings, and experiment with the delay in the presentation of each cue in accordance with the realistic times of sensory processing of different modalities, and of course, following the restrictions of the experimental platform.

2.2 Experimental Setting

We intend to test the temporal aspects of multimodal interaction by grasping. Since at present we have available only a mobile robot the experiments are restricted to a two-dimensional task of reaching a target. Based on earlier findings [2] two complementary sensory cues are sufficient and necessary for reaching, as well as for precision grip of the robot. An example for complementary sensory cues are proprioception and vision. In this application, the proprioceptive or self-motion information is the angular deviation of the head direction of the robot from the initial position. Vision data are used for spotting the landmark or goal direction.

The heading direction is defined by the output potential that is generated after the integration of both cues. The robot will typically find a compromise between target direction and free of obstacles space. The DNF model would supply a smooth solution of this problem, once the model parameters are tuned for the particular application. For tuning of the parameters a computer simulation is used. One of the reasons to choose for the dynamic neural fields model for sensory interaction is that it uses a window of time to combine all sensory stimuli and make a decision accordingly. Experimental studies of sensory integration propose that there is a window of time during which the stimuli are integrated for producing a perception of a unitary sensory event [12,19,5,16,20,24]. We intended to vary the size of the temporal window of the dynamic neural field model to find out whether there is an optimal window for integration for the particular sensory cues. Since the window of integration corresponds most closely to the time constant of the neural field model, its change will produce a linear dependence. At this stage we did not found a reason to change it to more complex (nonlinear) function: Instead, the window is defined by the necessary processing time for the visual and the proprioceptive cues and from the guidelines from experimental studies.

Our hypothesis is that the delay in activation caused by each of the sensory cues may cause or contribute to imprecise motor behavior. With the following experiment we are going to test the impact of the delay in the activation caused by each of the sensory modalities. We experiment with different delay intervals.

Each cue was delayed with different time interval when a goal finding task was performed. In figure 1 are shown the response times for movement direction. The visual cue delay causes longer response time.

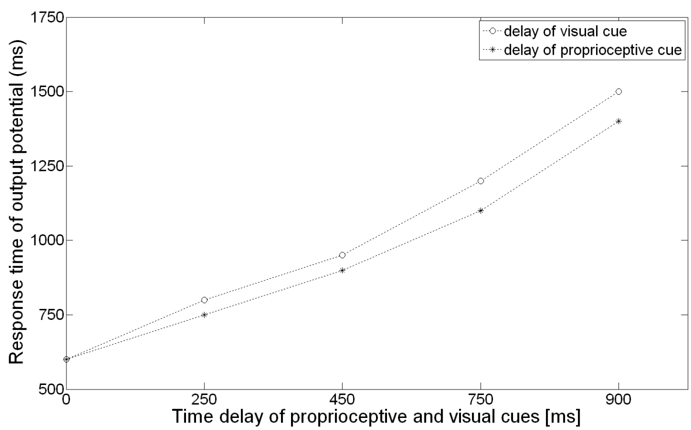

Fig. 1. The time to generate the output potential when each cue is delayed

To get further information on the delay effect of each cue, the experiment of changing heading direction for three successive steps was carried out.

Several tests with a simulated robot that performs target following task were made. In each test the target was moved so that the heading direction of the robot changes with different angles. Figure 2 depicts trajectories with a change of the heading direction correspondingly with 5 - 15 - 25 and 15 - 30 - 50 degrees. Figure 2-top shows the output potential of the second trajectory, and Figure 2-bottom shows the two trajectories in polar coordinates. Polar coordinates representation was chosen, because it corresponds to the actual movement of the robot, from its egocentric perspective. Several experiments were made to compare the effect of changing heading direction by different change of the heading direction when there was no delay, when there was a delay in the proprioceptive cue, and when there was a delay in the visual cue. Delay of the proprioceptive cue has less effect for generating the new heading direction in all experiments. The experiments differed in the sharpness of change in the heading direction, when both cues have the same period of delay, and the neural field parameters are constant for both cues.

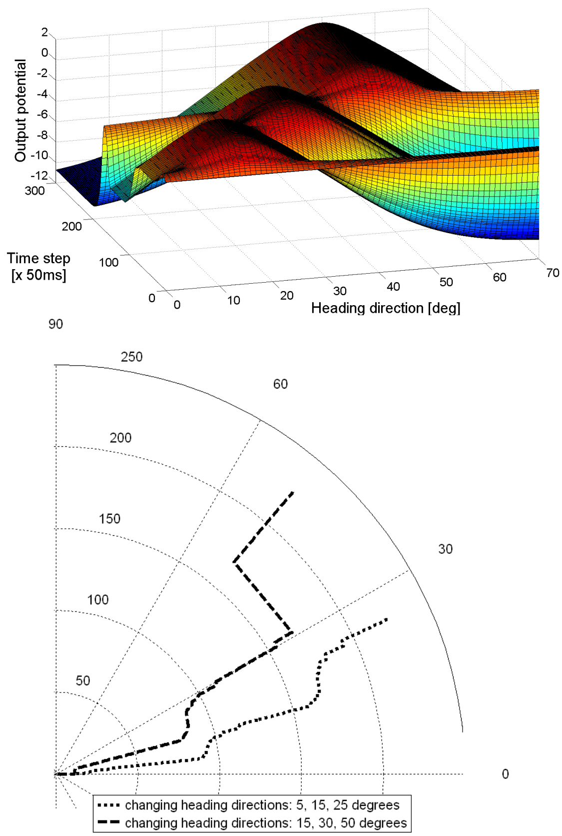

Fig. 2. Top:The output potential with HD changing with 15 - 30 - 50 degrees, bottom: the trajectories of the robot in polar coordinates with heading direction changing correspondingly with 5 - 15 - 25 , and 15 - 30 - 50 degrees

Experimental data from [27] show that although this is true in general,the precision of movements is determined differently by the visual and proprioceptive cues for depth and azimuth motion. Proprioceptive cue is more precise when the depth (distant goal) is targeted, and vision is more accurate in proximal (moment to moment) movements. To simulate this effect, the weight parameters of the neural field model were tuned to correspond to the variances for movement accuracy as found by Van Beers at al. [27]. Figure 3 shows the change of heading direction of the robot with tuned weight parameters of the neural field model

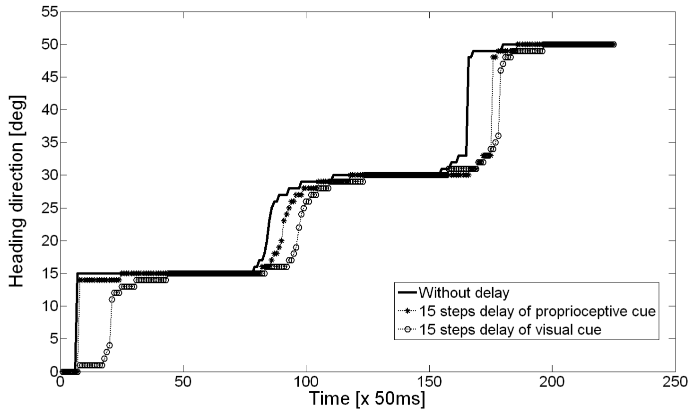

Fig. 3. Heading direction of the robot with and without delay by changing the target direction from 0 to 15 to 30 to 50 degrees. The 3 lines depict the change of heading direction by sensory integration without delays in the cues, and with delay with 15 steps of each cue.

in the cases of no delay, delay of the visual cue, and delay of the proprioceptive cue. Since this result is in consensus with the experimental studies [27,15,3], we intend to use it for grasping behaviors in robot for training of autistic children.

3 Robot Experiment

For the robot simulation an e-puck robot was used. The e-puck is a two-wheel mobile robot that was originally developed at Swiss Federal Institute of

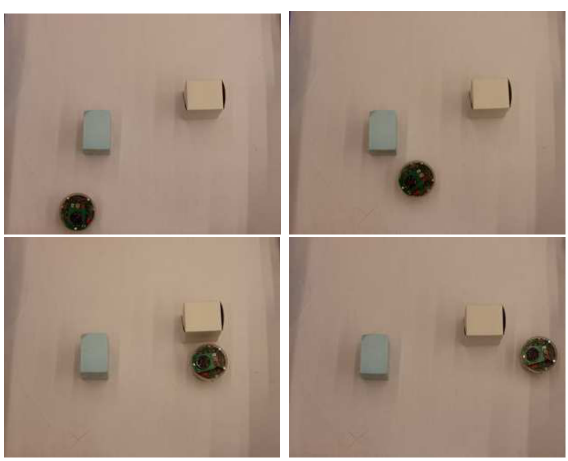

Fig. 4. The example path of the robot in an unstructured environment is shown in the sequence of pictures from left to right and top to bottom

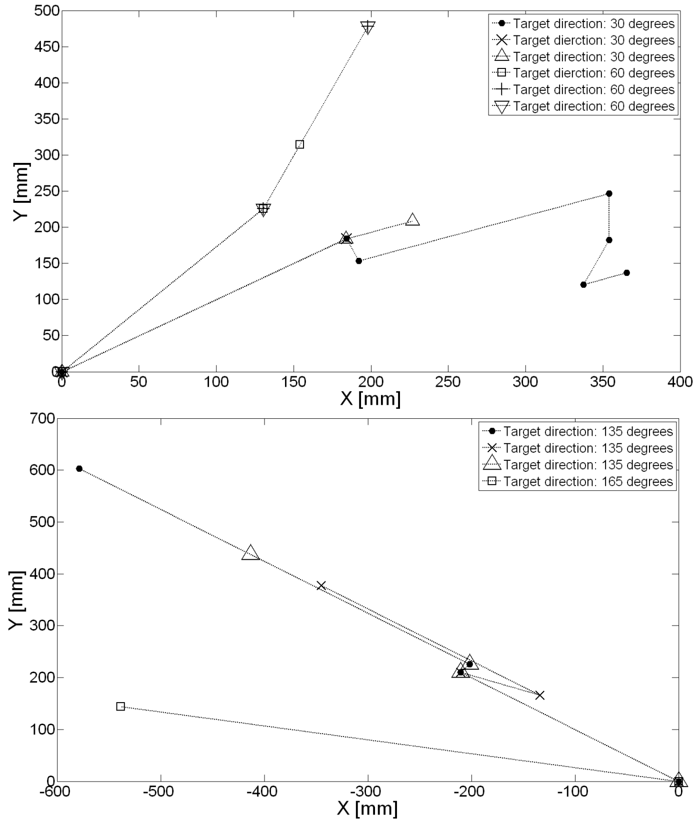

Fig. 5. Trajectories with target directions of: top - 30 and 60 degrees, bottom - 135 and 165 degrees, used to validate the model on a physical robot

Technology (EPFL) [6]. The robot is equipped with dsPIC processor. It is equipped with infrared sensors (IRs) that were used to derive the information about the turning angle of the robot. The free from obstacle space determined the possible direction of the robot for the next moment to moment movement. Vision was used to determine the target direction of the robot.

The experiment was divided into two parts: model validation and the hypothesis testing. We need to validate the model on the real robot because the DNF model parameters might differ by computer simulation and robot experiment.

3.1 Model Verification

To validate the model a task of searching for a randomly changing target was designed. The polygon shaped arena contained several objects that served as obstacles (figure 4). The heading direction was detected with respect to the initial position of the robot: the zero degree direction was chosen to be at the positive

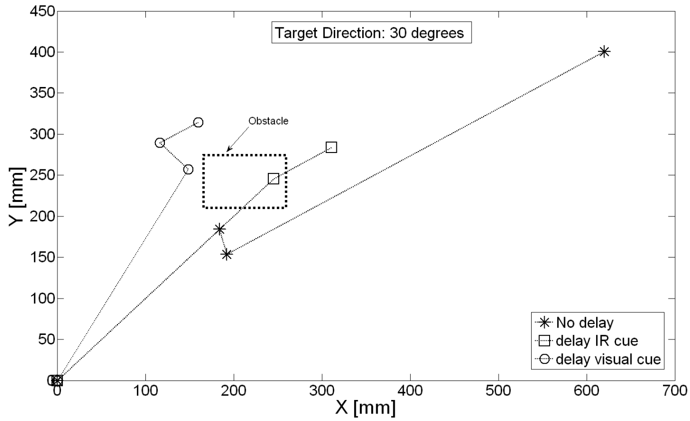

Fig. 6. Robot trajectories from sample experiment with no delay, delay of the IR cue, and delay of the visual cue

x-axis and the angle was measured counterclockwise. The target position was randomly changed each time after the time window for integration has passed.

The target searching task was chosen to not only set up the right values of each parameter of the neural field model, but also to test the sensors and the low-level control of the robot.

Based on the initial parameter values from the simulation,the robot found target and avoided the obstacles after few trials. Figure 4 shows an example robot path while performing this task.
The results from a sample test are depicted in Figure 5.

These results show movement with no added delay for the sensory cues. The time window was defined to be 550ms, since the sensory processing for this robot and control program is that large at present. The model is quite robust because e-puck can find any target direction. Moreover, the results in each target direction are similar.

The influence of each sensory cue on the output potential is tested after the experimental scenario was simplified by using only one obstacle in the arena, as shown in Figure 6. With this simplification the influence of any artifact on the outcome of the experiment is excluded. Without delay in the sensory cues, the robot can avoid the obstacle and reach the target direction in (right upper corner in Figure 6).

When the delay was added to the infrared sensor or to the visual input, the robot took different trajectories. Depending on the distance of the obstacle and the speed of the robot, changing the delays had different effects on it. Figure 6 shows three sample trajectories of the robot: without delay, with delay of the IR sensory cue, and with delay of the visual cue, respectively.

The delay of IR cue resulted in a collision between the robot and the obstacle. When the visual cue was delayed, e-puck started to move in arbitrary free direction until the visual input was received, without hitting to the obstacle.

4 Discussion

We investigated different temporal aspects of multisensory integration on the motor behavior of a robot, namely the effect of the size of the integration window and the delay of different sensory cues. DNF model was used to guide the robot movements, because it contains two parameters which, as we have shown, can simulate the effects of both temporal parameters: the influence of the interaction window and the delay in the sensory cues. The interaction window simulates the time for relaxation of system dynamics to the next fixed point, i.e. it isolates moment to moment multisensory integration. Using this property, we can delay each of the sensory cues and keep the integration within the span of the behavioral window.

The results show that delay of the proprioceptive cue has less effect on close interactions, while visual cue will have less impact on distant target finding.

The DNF model requires a certain time to generate output potential. When there were three successive changing directions the outputs were different when adding the same period of delay to each cue, single cue per trial. Implementing the model on physical robot showed that sensory integration with DNF model provides realistic behavior except for the length of the sensory integration window that has to be tuned according to the restrictions of processing capacity of this robot. The DNF model insures human-like decision making and smooth motion when different external stimuli are present. However, the unreliable sensory information can result in totally different behavioral solutions when the robot started from the same starting point in the same arena. Unrepeatable behavior may be caused by detection failure of the sensors or imprecise tuning of the parameters of the DNF model. The infrared sensors of e-puck robot are sometimes too sensitive to detect the obstacles in the environment, or sometimes they cannot detect anything when the robot stays too close to the obstacle. This results either in robot departing from the natural path or in a collision with an obstacle. To fulfill our ambition of simulating the sensory integration process by autistic people, we would need a more advanced platform, and we are in process of purchasing such. However, the obtained results with the current restrictions are very promising.

Our initial hypothesis was that a bad timing in sensory integration causes poor motor performance in children with autism. Masterton and Biederman [18] have shown that children with autism relied on proprioceptive feedback over visual feedback to modulate goal-directed motor actions, including reaching and placing objects under conditions that required adaptation to the displacement of a visual field by prisms. This finding might be indicative of a perceptual deficit resulting in poor visual control and visual sequential processing [18]. Leary and Hill [17] argued that motor deficits of autism can be not peripheral, but central to the development of children with autism and to have significant impact on the development of higher cognitive atypical behaviors that include unusual sensory or motor behaviors, in addition to social and communicative differences. We aim to extend our integration model to robot simulation of behavior of typically developing and autistic individuals, and use it for behavioral training of autistic children.

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