Models for Biological Motor Control: Optimality Principles

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Abstract

The understanding, how human controls there bodies to perform different operations with here extremities, is a central research topic for nearly 70 years. The human body has a high number of degrees of freedom which all can used for task execution. The central nervous system (CNS) processes also a lot of sensor information and handle as well external disturbances. For example there can be noise on the signal between CNS and sensors. In spite of these circumstances we can still achieve our task goal. In this paper different control schemes will be summarized, which can produce similar results in quality compared to biological behavior. This will be proven by presenting results of different test series. The resulting computational models can be used to improve the control of robots and also allow more detailed view to our biological motor control. Even if these concepts can reproduce the human behavior, the biological mechanism of motor control is still not fully understood.

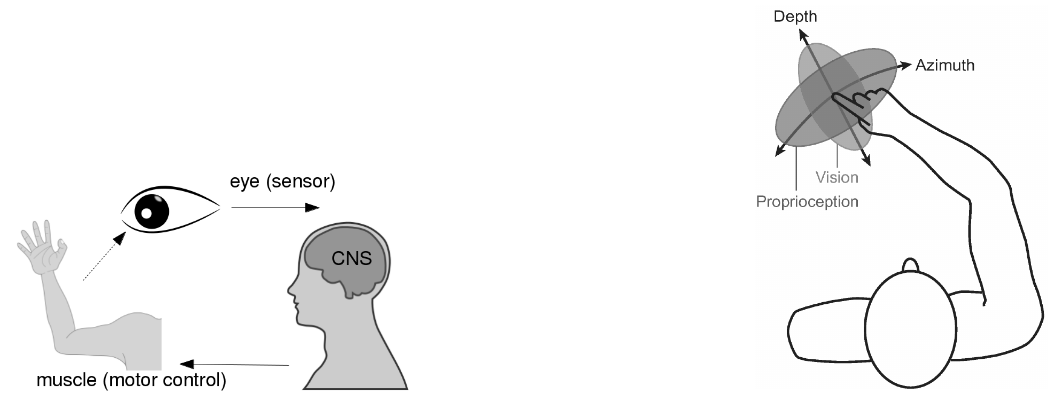
1 Introduction

The movement of biological lifeforms gives the expression that to move in this way is an easy task. They can easy react to changes of the environment and handle as well unexpected situations. The complex system which is behind this control is still not completely understood. Researches still tries to create computational models which works with the same principles as the biological equivalent or producing results with a similar quality. These models can be used to verify the knowledge about the biological systems as well as for improved robotics control. Humans are be able to execute tasks, for example take a glass of water from table, easily where in robotics this can be a hard to achieve. It is possible to create a robotic arm largely identical to the human arm in the number of degrees of freedoms, but to control it still can't done in the same quality.

The basic biological model of motor control consists of three components. The first one are sensors, for example we can see in which position our arm is, another sensor input is the propriozeption of the position of our arm. Based on this sensor input we can plan and execute movements. This is done by the central nervous system (CNS) which includes our brain. The planned control commands for the movement are sent to the biological motor, the muscles. This model is also called *sensorimotor*.

Figure 1a shows a simplified view of the sensorimotor principle. We have an eye as sensor input which sees the arm position. The central nervous system use this information to control the muscles through sending neuronal control commands. The muscles react on these signals and through contraction the arm positioning got changed.

The processing of the sensor input and the control of the movements in an accurate way is a complex task. Not only to plan the movement itself, which means how should an arm movement to achieve a specific plan, but also to estimate the current state of the arm and to control the movement itself. The environment is another challenge for biological motor control. Human can learn to react to the dynamics of the reality for example to sidestep obstacles which occurs in the movement trajectory.



(a) (b)

Figure 1:
a) show the simplified model of a sensorimotor. The eye is the sensor input. Based on the sensor information processing, the CNS control the motor movement, in this case the arm.
b) show the precision of different types of sensors. In this figure the vision 'sensor' delivers more accurate information about the depth. The proproception 'sensor' instead is more accurate in the azimuth (Images taken from [1])

The estimation of the current state depends on the information the sensor delivers. A problematic aspect of sensor analysis is the inaccuracy of sensors. Each sensor has some incertitude and process information in a different way. An another problem are external disturbances also called sensor noise. The latency of sensors are also different. Combined with multiple sensors the state estimation has to evaluate all these information to calculate accurate current state.

After processing the sensor input a movement can be planned and executed through the motor control. A human body for example has a high number of degrees of freedom with all the joints in the skeleton model and the muscles and sinews to control them. Thus, movement can be done in a lot of redundant ways. The execution of the movement by sending a motor command can be also corrupted by noise. When then noisy signal getting processed the movement isn't equal to the desired one.

The motor movement can be also be affected by the dynamic environment. When the environment is changed during the movement so it can't be executed with the desired trajectory humans can learn to compensate these changes. For example with an internal representation of the environment, we have a prediction about the movement. This inverse model detect changes when the execution doesn't match the predicted movement. This information also can be used as training signal. In this way we learn to react to specific changes in the environment, also when they are not expected. In robotics it is still hard to execute a task successful when the environment is not well known or changes suddenly. The control of the environment disturbance is also called impedance control.

This paper describes some actual approaches and proposals which targets the different components of motor control from a computational perspective. The main source of information of this paper are from the paper 'Computational principles of sensorimotor control that minimize uncertainty and variability' from Bays and Wolpert [1] and from the second paper 'Optimal feedback control as a theory of motor coordination' written by Todorov and Jordan [5].

In the second chapter of this paper the processing of sensor input is described. Which problems occurs and how they can be solved. In this case two principles getting discussed in more detail. The topic of the third chapter is the motor control itself, the basic control principle and the more advanced minimal intervention principle. The fourth chapter describes the impedance control and how it can be handled.

2 Sensory feedback

To plan a movement an accurate knowledge of the current state is required. This state estimation depends on sensor inputs which delivers different types of information. For an accurate state calculation we have to handle two aspects of the sensor feedback. One aspect is the combination of multiple sensor information, how can they combined in an optimal way as the sensors have a different precision also related to sensor noise. This is described in the first section of this chapter. Another aspect is the sensory signal itself, how can we optimize a sensor signal. Some approaches to prepare sensor signals are described in the second section of this chapter.

2.1 Optimal integration

When we have multiple independent sensors we have to integrate this information in an optimal way. For example to estimate the current position of an arm we have two available sensor information. The first one is the 'visual estimate location' of the arm, which can be provided by human eyes or from a technical perspective a camera. The other sensor is the 'proprioceptive estimation', which is an internal perception of our extremities. In robotics this information can be extracted from sensors in the mechanics. A state estimation can consists of different parameters, in this simplified view of an arm position we have two dimensions one is is the depth the another one the azimuth of the arm. To estimate the current state we have to process these two dimensions based on the two sensor input. Each sensor has for each dimensions a different precision, in experiments it has been showed that in this case the visual localization delivers better results in the azimuth dimensions instead of the proprioceptive localization which is more accurate in depth. Figure 1b visualize these relations.

For the state estimation we can now combine these sensor information based on their precision. This can be expressed as $w_p P + w_v V$, P is the value of the proprioceptive estimation sensor information and V the visual based location. Each sensor input get weighted by their precision w_p and w_v. With this simplified handling we can combine multiple sensor input in an accurate way for state estimation.

This first approach can be used when multiple sensor information are available. When we have only one sensor input the state can be estimated using the most probable state. To integrate this single sensor in an optimal way it is possible to use the history of the sensor information. The history of the the sensor is represented through the last estimated state. To calculate a new state we can integrate the last state information with the new sensor information to make a more accurate estimation. This can be done by using a Bayesian probability model. The background of this approach is for example, that an arm is normally placed in front of a body. This probability can be used as initial start point of the calculation. New sensor information can update the actual Bayesian model. When the arm movement ends with the arm still in front of the body the next probable state of the arm is also in front of the body. This Bayesian model looks like this:

$$P(\text{state}|\text{sensory input}) = \frac{P(\text{sensory input}|\text{state})P(\text{state})}{P(\text{sensory input})}$$

The *prior* $P(\text{state})$ represents the current predicted state before sensor input is processed. The *likelihood* $P(\text{sensory input}|\text{state})$ is probability that sensor input ends in a specific state. Multiplying the *prior* with the *likelihood* ends in the *posterior* estimated state $P(\text{state}|\text{sensory input})$.In this normalized 'so that sum of the probabilities over all possible states sum to one'[1]. The posterior can be used as new prior belief so these model can be updated during processing. This also works with multiple sensor inputs and weights the prior and the likelihood related to their precision.

From a biological perspective also a neuronal network can compute results similar to the Bayesian approach [3]. An advantage of the Bayesian model is that it can be easily updated when new information are available. A Bayesian probability can also be easier calculated as a complex neuronal network simulation from a computational perspective.

This Bayesian model also has been investigated through experiments in which subjects has to made corrections to a movement based on visual feedback. During these test series the movement distance varied and based of the errors and corrections values for the Bayesian model has been created similar to sensor weights in the first approach [1].

2.2 Predictive filtering

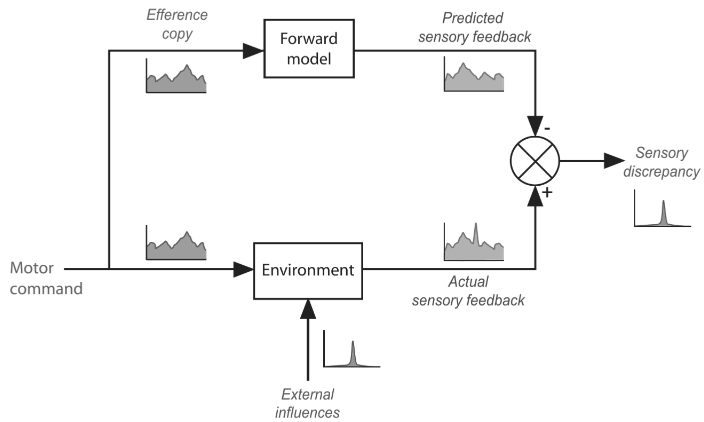


Figure 2: This figure shows the sequence of predictive filtering by a forward model. Based on motor command the forward model creates a predictive sensor feedback which should induced from the executed motor movement. This predicted feedback is compared to the feedback from the real sensor. The difference is the not expected sensor feedback. (Image taken from [1])

When a movement get executed it automatically induce a sensor feedback. The position for example of an arm is changed and this is also included in the sensor information. These changes are expected, but for example when an obstacle occurs in the movement trajectory, the sensor information delivers not expected information. With predictive filtering[1] the sensor signal can be cleaned up so we can analyze the sensor information which is not expected. In other words predictive filtering removes sensor information which is generated by own movement. With these extracted information we can for example identifier external disturbances.

Predictive filtering works with an internal forward model. This forward model generated a predictive sensory feedback, when we send our motor control we expect through the motor movement the next sensor feedback delivers values resulted by this movement. The forward model contains an internal representation of the environment (as sensors deliver information related to the environment) and and can be used to predict the sensory signal in the near future. The differences between the predicted and the real sensor feedback are external disturbances which are not expected during the movement.

Figure 2 visualize this behavior. Based on the motor command an expected sensor feedback is generated based on the feedback the command should induce in the real environment. This predicted feedback is compared to the real sensor feedback. The difference represents the not expected sensor feedback. For training purposes this model can also used to show imperfection in the current implemented forward model.

To investigate the existence of such an internal model and its behavior subjects have, in an experiment, to reproduce a pressure which was applied on one finger. When the subjects try to reproduce it with a finger from the other hand they overestimate the pressure. When they use a joystick to control the pressure this behavior didn't occur. This experiment shows how the internal prediction is different between self generated pressure and the external applied pressure. From a biological perspective this misinterpretation also happens with schizophrenia[2] patients, they have the feeling that their own actions are controlled by a third person and not by their own. This is an indicator for malfunctioned predictions the patients has about their movements, so it looks for them like an external force does it.

3 Motor control

Based on the cleaned up sensory input a movement can be made, from the biological perspective the motor control has to handle neuronal noise and non constant reaction of the muscles. Each 'motor' in the complex biological system also has it's own idiosyncrasy and react in different ways. Through this behavior the movement execution becomes variable and require a control mechanism for achieving the correct movement. There are also a lot of different possibilities how a movement can be done. For example the human arm with the hand has a lot high degree of freedom with all joints it has. There exist different optimal control strategies the simplest one is known as optimal trajectory planning.

3.1 Optimal trajectory planning

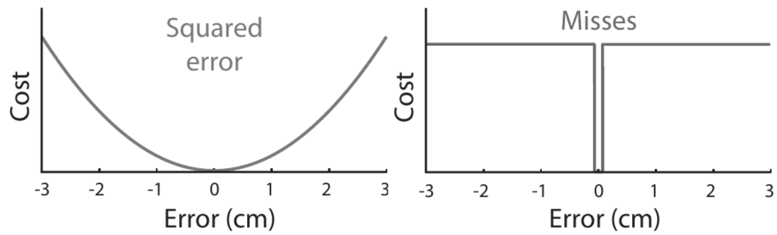


Figure 3: In this figure we see a visualization of two cost functions. These cost functions describe how errors get treated in optimal control by calculate a cost value related to the errors. (Image taken from [1])

For an optimal control the 'costs' of a movement can be minimized. The costs can for example be expressed as minimal change of all joints in the angle. Other factors are the duration of the movement or the required energy.These factors can be weighted in different ways based on the task to execute.

The 'cost' function can for example be defined as a simple squared based function which maps the costs to errors in this way. Another possible definition calculated the costs equal out of a small valid range. The definition of the cost function also influence the execution of the movement. For different tasks the different functions deliver different quality of results. Figure 3 show a squared function of costs on the left side and in the right side a function which rates all errors with the same costs. The optimal trajectory planning tries to minimize the long term costs of a movement to achieve an optimal result. The trajectory planning results in the optimal static trajectory $y^*(t)$.

A disadvantage of this optimal control scheme is the reaction to disturbances. The movement get executed with a static trajectory and has to follow a static set of constraints. This means each deviation from this static path may get corrected also when no intervention is required for a successful execution of the the task. In other words it tries to execute a movement with high accuracy under the minimization of variability during the movement. The problem of this approach it also want to compensate disturbance when it is not required. A movement can be achieved in different (redundant) ways and some deviations prevent the movement from success. We can observe this as humans does not exactly repeat a movement twice. This leads us to the next control principle the optimal feedback control.

3.2 Optimal feedback control

In the optimal feedback control there is no difference between planing and execution step, feedback controllers can follow a weak scheme of constraints but also this is not a requirement. As the name implies this control model uses the sensor feedback to control the movements in a dynamic way. The trajectory is not static as with optimal trajectory planning but can be modified during the movement process. The optimal feedback control starts with a stochastic dynamic trajectory and based on a feedback control law this trajectory get modified.

Almost all of these models tries to minimize the endpoint variability, which has the advantage that it can be easier estimated from sensory feedback. When the calculations are based only on the endpoint variability, only the errors related to the endpoint position has to monitored. The target of optimal feedback control is to determine the optimal controller $u^*(t)$.

The wide range of variability of a movement can be still problematic. Almost all proposed solutions for this problem are based on a stochastic optimal control models, which takes responsibility of the motor noise. In the following section an optimal feedback control principle called 'minimal intervention principle' will be described. The basic idea of this principle is to ignore errors in not relevant task dimensions to minimize required corrections.

3.3 Minimal intervention principle

The minimal intervention principle [5] is based on the idea that variability is allowed in a wide range of tasks when occurs in a task-irrelevant redundant dimension so no intervention is required. The idea behind this strategy is the limitation to perform the task in an optimal way so the most important part is the successful execution of the task In the minimal intervention principle there is no gain to make correction in task-irrelevant dimensions because the only goal is to perform a task in optimal way. The control law for this principle ignore all task-irrelevant deviations and react only when the task goal is endangered.

The variability is a deviation from the current trajectory. With optimal trajectory a deviation is treated as an error, optimal feedback control can evaluate this deviation. As there are a lot of possible way to execute a movement this deviation can be part of an alternative redundant way. These redundancies can be categorized in different types. The following section describes these types variability is possible and also the behavior of the minimal intervention principle in the different cases of variability.

3.4 Redundancy

The are different types of redundancy, for example all possible movements an arm can made to achieve a specific task are defining a redundancy set. Or multiple trajectories which ends in an identical position. During the motor control it is not relevant which parts of the possible redundant movements getting executed, when they ends in the same result. There are also some other types of redundancy for example based on the history of the current state.

Mechanical redundancy

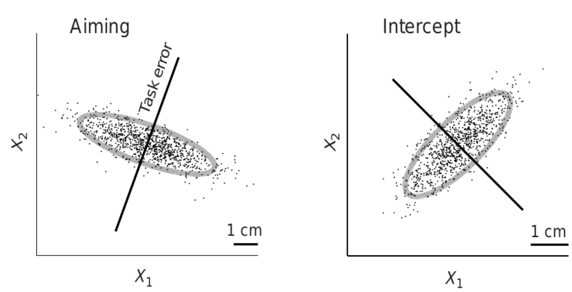
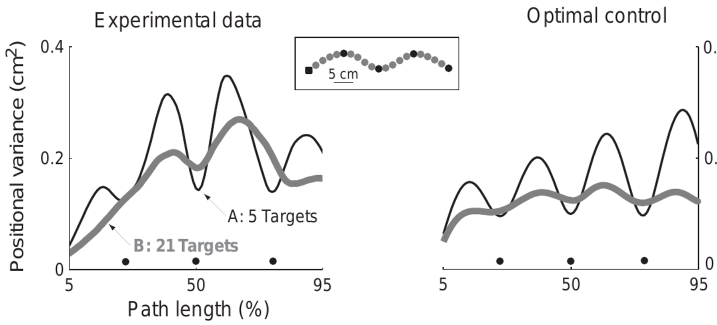
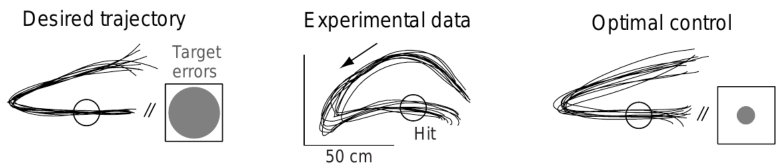


Figure 4: The left side of these figure shows a simulation of a simplified pistol aiming task. The right side shows a similar kind of simulation with the movement goal $X_1 = X_2$ (Image taken from [5])

Mechanical redundancy can occur in actual state, related to the task goal. So the task constraints are satisfied but the mechanical state of for example joints can be different. An experimental example for these behavior is a pistol aiming task [4] when different angle of joints does not influence the alignment of the pistol axis with the target. In figure 4 results from a simple aiming task simulation are showed on the left side. The X_1 and X_2 has to end on a specific 'line of sight'. The task error line is a visualization of the used cost function. As seen on the figure most of the points are on this line of sight orthogonal to the task error function. On the right side of figure 4 an alternative simulation is shown. Both X_1 and X_2 has to end in the same position $X_1 = X_2$. In this case the sample space is also in optimal alignment related to the cost function. So the simulation shows the allowed mechanical variability under the task constraints is used, but the task error is still minimized with an optimal feedback controller.



(a) This figure shows the trajectory variability during a movement through a sequence of targets. The left side shows the experimental data based on a test series with subjects. The right side shows the results created by using the minimal intervention optimal control scheme.



(b) This figure also show trajectory variability but with the task to hit a target with a ping pong ball. The left side show the trajectory created by optimal planning and the related target errors. The middle part shows the data from the test series. The right side shows the trajectories handled by minimal intervention control. The circle mark the constraints in which a ball has to released from hand to hit the target.

Figure 5: Trajectory redundancy (Image from [5])

Trajectory redundancy

Trajectory redundancy means there are multiple possible trajectories to achieve a movement. In figure 5a on the left side experimental data is shown resulted from an experiment in which subjects have to make a planar arm movement through a sequence of targets. For this experiment two conditions are used the first one *A* has five targets with a wide space between them. In condition *B* sixteen additional targets are added along the average trajectory produced with *A*. With optimal trajectory planning and a desired trajectory the was no difference between the two conditions. The desired trajectory can not benefit from the possibly variability, the the optimal feedback control instead (as shown on the right of figure 5a) uses the variability for a more efficient movement. With a higher count of targets the possibly variability is lower because there is less room to reach the task goal, the minimal intervention principle then restricts the variability. The minimal intervention principle also first starts compensating when the task goal is jeopardized. No effort is wasted when it is still possible to achieve the goal.

Another example of trajectory redundancy is shown in figure 5b. The data is based on an experiment in which subjects has to throw a ping pong ball to hit a target. This task is particularly interesting because the movement of the hand has no relevance to the trajectory of the ping pong ball after it has released from hand. The release point is constrained to a specific range (marked with a circle). The desired trajectory on the left side minimizes all variability to a strict movement. For a dynamic movement like throwing a ball accurately this ends in a higher amount of target errors. The real experimental data shown in the middle has more variability, humans doesn't throw in an identical way twice, but still be able to hit the target. The resulting trajectory of the optimal feedback controller allow variability in the movement, especially after releasing the ball, these movements are closer to the reality and also has a smaller amount of errors as the optimal planned trajectory. In these experiments we clearly see the advantages of the optimal feedback control principle. Humans act in a similar way as the minimal intervention principle, so corrections to the movements are made slightly and only when they are required.

Object manipulation

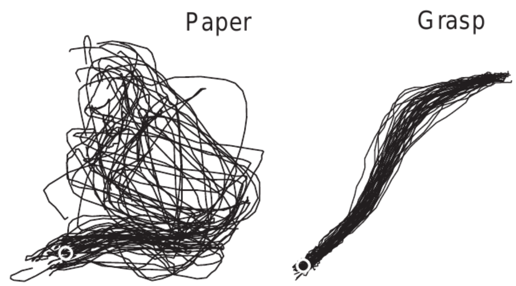


Figure 6: This figure shows two experiments related to object manipulation redundancy. The left side shows the variability of the hand movements when subjects has to turn a sheet of paper to a paper ball. The right side shows the variability for grasping a cylinder. (Image taken from [5])

The object manipulation redundancy is the most complex form. The state of the controlled object also controls the task result. This dependency means that the complete history interaction which lead to this state can be relevant. In [5] the authors conducted an experiment with five subjects. The task was to turn a sheet of paper into a paper ball and leads to an interesting result, the observed variability was higher than expected. These experiments also show the variability isn't high for all tasks. For a simple grasp of a cylinder the results are nearly identical. Each subject has a different way to crumble up a sheet of paper but show an identical behavior to grasping a cylinder. Figure 6 shows the difference in variability between crumble up a paper ball and grasping the cylinder. The variability for grasping a cylinder is much lower each subject does it in a similar way instead of turning a sheet of paper to a paper ball where each subject has a different way to do it.

From a computational perspective the hand looks during the paper crumbling total dysfunctional, but still with this high degree of variability humans can easily perform the task. This variability occur through the different possible solutions based on the current state. Humans are able still to find a solution to perform the task. For a computational model it is hard to determine the right direction in these redundant dimensions. In the 'grasping cylinder' task the variability is much lower, so not all types of tasks have this complexity to handle. In this case the optimal feedback controller also delivers results similar to the human behavior[5].

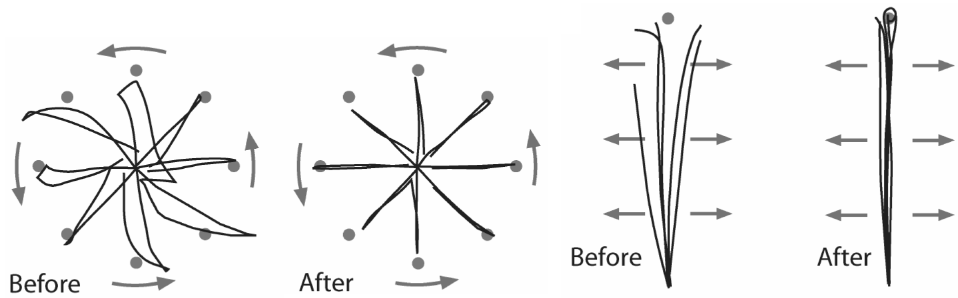
4 Impedance control

To work against systematic disturbances for example to walk in a straight line during strong wind we can learn to do a compensation movement. With these corrections we're able to still reach our task goal this type of control of external disturbances is also called impedance control. One proposed strategy to handle this problem is the usage of an inverse model. The inverse model is an internal representation of the dynamic environment which computes for a requested movement the right motor command signals. A dynamic change in the environment causes to an inaccurate movement, but these errors can be adapted in the inverse model to represent the new dynamic environment.

As experimental investigation the influence of state dependent forces have been studied. These experiments shows that force fields causes large deviations in the planned movement and requires corrective movements to achieve the movement goal. These experiments also show that with more practice the subject learns to respond in the right way to this disturbance and can stabilize the movement with a compensation movement.

Figure 7a shows an experiment where subjects has to execute a movement along a path between the center and points aligned in a circle round the center. With external influence the movement is inaccurate but over time the subjects improved their correction behavior and can execute the movement in more accurate way.

The inverse model works when the influenced of the environment are predictable. In other scenarios, for example to drill a hole in a wall with the right angle, the corrections movements required can not



(a) (b)

Figure 7:
a) shows an experiment in which subjects have to make a movement from the center of a circle to points on circular line. The arrows show an external disturbance which corrupts the movement. The subjects has learned to compensate the disturbance and can execute the task accurate at the end of the test series.
b) shows a similar experiment but here the task was to make a movement in a straight line. The subjects compensate the disturbance with a higher stiffness.
(Images taken from [1]

be estimated. In this case a strategy is to increase the stiffness through co contracting the muscles, so the position of the arm get stabilized. In an experiment subject has to make a movement in a straight line corrupted by external controlled force. To response to this applied force the subject increase the stiffness to minimize the influence this is shown in Figure 7b.

Impedance control can improve the response to undesirable events, but still can't be perfect. For possible disturbances strategies can be implemented and trained and works for some kind of 'unexpected' events. Still these disturbances are some type of expected disturbance, such as typical forces which occur during drilling. But for example when get bumped during drilling it's hard to complete the task correctly. To handle each situation hundred percent correctly we have to make a hundred percent correct prediction about the future which is impossible.

5 Conclusion

In this paper we have discussed different aspects of the human motor control and how in can reproduced in a computational way. The sensor information can be prepared through optimal integration models which estimate the state with weighted signals. The last known state can also be included in this estimation. To extract only the relevant information of a sensor we can use the predictive filtering to exclude predicted information from the sensor feedback. For motor control we have discussed optimal control models. With optimal trajectory planning we get a desired trajectory to execute a task, but we have also showed that we get better results when we use optimal feedback control for movement control. We have discussed the minimal intervention principle which is an optimal feedback control focusing on optimal task performance. At least we have discussed impedance control to handle disturbance in a dynamic environment.

These computational models can be used to improve the behavior of robots to achieve a similar flexibility as humans. Unfortunately these models are still not prefect. We can produce results which looks similar to the behavior of the biological model, but still robots have problems to adapt unknown environments. Human motor control depends on internal predictions which can also leads to errors. Humans are be able to quickly adapt changing situations and improve there control. The computational models can also be trained and can learn but didn't provide a similar flexibility.

Further knowledge of the neurophysiology may reveal an unified system to reproduce the natural behavior of motor control and also maybe can adopted to optimize technical task execution. For robots it is often a requirement to be very precise, the human behavior instead allow a wide range of inaccuracy to execute a task. For an optimal control model for robotics we require a deeper knowledge of the biological principles but also require an adaption which works especially under specific requirements. To control robots with a similar flexibility to humans but without human mistakes is challenging topic.

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