Computational Neuroscience
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Week – 11
Lecture – 52

Lecture 52 : Models of Short Term Plasticity

Welcome. So we have been discussing short term depression and how that is implemented in networks to explain phenomena that we see in terms of adaptation at short time scales. So we had discussed a specific example in detail which is the stimulus specific adaptation or deviant detection and we discussed some others which is sound level statistics adaptation to that and adaptation in the visual system to contrast. So now actually the important point is that can we implement this kind of short term phenomena in models that we have discussed in terms of receptive fields of neurons. So if you recall when we did the spike triggered average we had discussed it in this way that if there is a stimulus x_t which is going through a linear timing variant system which has an impulse response h_t and then it is providing an output y_t which is what we were mentioning as the membrane potential of the neuron from which we are recording from as if akin to that this y_t. And so that is what we passed through the static nonlinearity which can be sigmoidal or otherwise.

So this then produces the driving function for the point process and so that is this λ_t and so that is driving the point process and we are getting spikes here. So that is our p_t that is summation $\delta(t - t_i)$ i equals 1 to let us say capital N spikes are occurring. So if we have to implement short term depression or short term facilitation in terms of this system that so we do not have that here at all. So if we need to incorporate that we will have to incorporate it by changing our y_t because x_t cannot be changed by us and the λ_t is already the driving function for the point process.

So whatever adaptation effect is there if we can get it into this y_t then we can have incorporation of the short term phenomena. So essentially what would be the short term phenomena this our p_t which is the spike train that is occurring let us say this is p_t and we have spikes occurring at time points t_i i equals varying from over a number of values. So if we see here whenever these spikes are occurring close by it would mean that the next spike would have a lower chance of occurring because of the synaptic depression if it were synaptic depression. So the further away you go the probability of that spike occurring is going to recover to its normal probability based on whatever stimulus is going on. So remember that one process driving the spikes is the stimulus and another process driving the spikes or altering their probability is the spikes themselves their own history.

So that can be incorporated with a feedback like this and that goes as an input to this entire non-linear function or the static non-linearity. So what do we need to do here that we need to change the membrane potential over and above or below I mean modulate the membrane potential that is derived from the stimulus based on whatever history we have had of spiking. So essentially we can have something like a kernel that is a recovery kind of kernel that immediately after a spike we reduce the membrane potential by a large amount or as we go further out the membrane potential will be unchanged based on whether there was any spike or not. For every spike we change the membrane potential by this function or basically we are essentially convolving this kind of a function with the spike train and feeding it back into y_t. So this particular function may be some shape r_t or r may be used for rate so let us give it some other name let us say c_t.

Now based on the shape of this c_t we can incorporate a variety of phenomena we can do facilitation we can do depression we can do a mixture of them and so that depends on fitting the model. So remember for the fitting of the model this h_t was derived simply by spike triggered average and at that time we did not have this particular part in the system. So now that we have this additional part the entire theory that we had discussed in terms of the spike triggered average to obtain something proportional to h_t that goes out the door. So basically now it is an optimization problem or I mean error minimization kind of problem or that can be approached in multiple ways either with gradient descent or maximum likelihood and so on. So that c_t function has to be assumed of some certain form to begin with h_t can be assumed to begin with the spike triggered average and nonlinearity also can be assumed to begin with whatever we get from the spike triggered averaging process and then do starting from this point we do a gradient descent on the error in between the data and the model.

The spike train rate of spikes or probability of spikes over time and the observed probability of spikes over time and basically reach optimal point based on some criteria and obtain the c_t and that actually improves our models both in the auditory system and the visual system like the STRF s and the temporal modulation functions for Retinal Geniculate Nucleus neurons Lateral Geniculate nucleus neurons and even visual cortex neurons this synaptic or history dependence improves the performance of the models by many fold. So this is an additional nonlinearity that is being included and so although now the estimation is different because it is now any standard mathematical optimization problem and it can be and it can be easily understood also in terms of the underlying phenomena that is causing the departure from the linear model and that is what rather what can be explained based on synaptic short term synaptic plasticity. So this is one way now obviously this can be extended further if we have simultaneous recordings and so essentially we can have a crosstalk of this h_t between two neurons back and forth and within themselves. So that sort of a model let us if we have a block this whole thing is a block now. So then the upper block here is like this this is the spike train output this is $p_1 t$ and this is our stimulus x_t which is going into one block as well as another block that is two neurons that is simultaneously.

Now we can have and if this is one and this is block two then we can have a feedback from two back into two or we can have a feedback from two back into one and similarly we will have two feedbacks from the output one this is $p_t 2$ we can have a feedback from here back into itself and we can have another feedback that goes and feeds into the other neuron. So it can be done based on simultaneous recordings. So all these kind of problems can be dealt with using maximum likelihood kind of estimation processes and indeed improve the only linear version of the models to quite a degree by including the different kinds of short term plasticity dynamics. So essentially what we have what we are trying to represent in these four cases are basically four different synapses one or rather four different processes of which two are synapses that are providing input to the other neurons that is sort of a recurrent connection to recurrent connections and there are two that are synapses that are being that are that are representative of synapses in the path of the input to that same neuron. So with this kind of short term plasticity approaches with by incorporating them in models of this nature we can build receptive fields even more concretely even more realistically which incorporates these short term phenomena.

So while the cost of this is with additional complexity the estimation process becomes more and more difficult or rather I mean there are problems of getting into local optimal points and so on although there are standard techniques you to be used to get out of such points you can still I mean there is no final way of saying until and unless some analytical solution can be obtained for this kind of problems. So currently we do not have and it is extremely difficult to think of a possible way to get the solutions for C_T analytically and so it is not just C_T it is also H_T it is also the non-linear function F_T and so on. So with this case of implementation of this short term plasticity let us just for a second talk about a little bit of what this C_t functions can be like at different stages and so if we have as we have already discussed this kind of a function C_t is simply like a recovery. So you this is the effect or modulation on the membrane potential on this axis and this is time from spike for every spike. So in the case of facilitation it is if you think it can be of this nature that is if you go further out you get lower and lower facilitation or you can think of it in this nature also with this which this is more realistic to have a C_t that is facilitatory.

We can have a mixture that is usually represented by this kind of a function. So if we stick to these kind of functions these particular kinds of functions then we do have possible analytical forms of them with maybe just a few parameters and not the entire function and that way we can simplify the problem a little bit. So this is a mixture and we can actually implement all of these very easily with different kinds of functions and parametric functions and make the estimation process easier. So with this we will conclude our discussion on models based on short term plasticity and next we will be discussing about other kind of examples and modeling of long term plasticity in to observe to explain different phenomena that we see. Thank you.