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Learning by geometrical shape changes of dendritic spines

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Abstract. The role of dendritic spines in neuronal information processing is still not completely clear. However, it is known that spines can change shape rapidly during development and during learning and these morphological changes might be relevant for information storage (memory formation). We demonstrate the impact of shape variations on electrical signal propagation via dendritic spines using a biologically realistic electrical simulation procedure. Basic properties of electrical signal transduction of single spines are estimated and approximated in relation to their individual shape features. Learning processes to adjust specific electrical properties are discussed and a possible mechanism is introduced.

1 Introduction

The input region of artificial neurons is often simplified by using a weighted superposition of incoming signals. But biological neurons display a nonlinear behavior with a large variability to modulate and integrate input signals. Besides the synaptic boutons which contact the cell body and the dendritic shaft, many types of neurons display synaptic boutons which are located on dendritic spines of specific geometry (see Fig. 1). Although the existence of dendritic spine is known for centuries [1], their precise functional role in the brain is still widely unclear [2,3]. Morphological studies revealed that the density and spatial distribution of spines, and also their size and shape are quite variable and can change during brain development and during learning processes within minutes or hours [4,5]. Whereas the geometrical properties of individual spines can be estimated by analyzing high resolution microscopic images [6,7], the influence of geometry on the signal transmission is not clear yet due to shortcomings of electrical measuring techniques in this small dimensions.

By applying a biologically realistic numeric simulation of neuronal signal transduction, which takes the relevant properties of membrane, ion channels and geometry under consideration, we are able to demonstrate the influence of systematic variation of spine geometry on the range of input signal modulation on a single spine. Using this

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approach fundamental electrical properties and their relation to geometric parameters can be identified and characterized. Furthermore, a possible role of this link between electrical and morphological features in a learning process is introduced.

2 Simulation Model

A simplified part of a dendrite with a single spine (Fig. 1 right) was used to study transduction of electrical signals arriving at the spine head to the stem dendrite. The geometry of the spine is reduced to four basic parameters: length l_n and diameter d_n of neck and length l_h and diameter d_h of head. The simulations are performed by a compartment model [8]. In contrast to other models [9,10] the spine neck is modeled by a number of compartments and not by a single resistor, in order to include effects of dynamics caused by the distribution of capacities along the spine neck. Thus, the spine is divided into 10 compartments (3 for head, 7 for neck) and the dendrite into 20 compartments. A special compartment is added to the dendrite to simulate proximal parts and the soma. In the first compartment of the spine head a glutamatergic synapse is integrated to simulate the synaptic input.

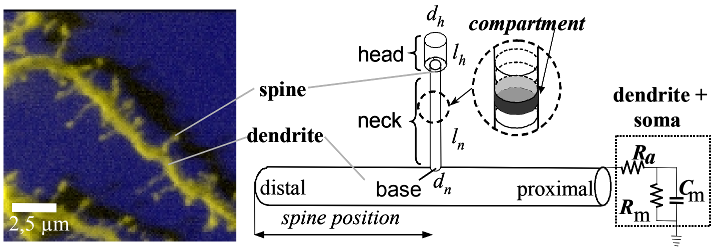

Fig. 1 Part of a dendrite with spines (left), Model of a dendrite with spine (right)

Electrical properties of membrane and environment are set to standard values (R_m = 0.333 Ohm/m²; R_a = 0.3 Ohm/m; C_m = 0.1 F/m², E_r = 0.07 V). The concentration of active ionic (HH) channels (only in spine head; neck and dendrite are passive) is set to a sub-threshold level. These values are kept constant during the simulation experiments. Investigations in which varying values were applied did not reveal qualitative differences in the results as long as the concentration of active channels was kept below threshold. Possible biochemical mechanisms of synaptic plasticity such as long-term potentiation and long-term depression (LTP, LTD) are not included since this study was focused on the role of morphological features. For numerical simulations of the compartment model the program GENESIS [11] was used. Data provision and analysis was done in C++ and MATLAB. All calculations were run in parallel on a Beowulf PC-Cluster using Linux.

3 Experiments and Results

3.1 Identification of electrical properties

An incoming spike at the spine head evokes a temporary change in membrane conductance. Depending on potential differences a current will flow and produce a postsynaptic-potential (PSP) which spreads through the spine and dendrite. The PSP could be observed at the junction of spine and dendrite. Fig. 2 illustrates the curves of membrane potentials for different spine shapes. On one hand the membrane potentials could differ significantly, on the other hand spines of different shape displaying nearly the same PSP were also observed (spine 2 and 3 in Fig. 2).

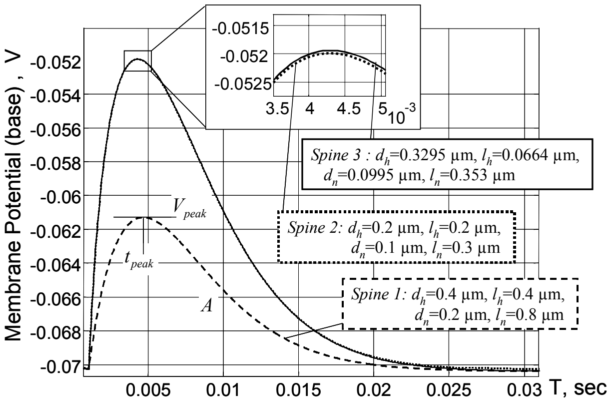

Fig. 2 Curve of membrane potential (PSP) on different spine shapes (see text)

Various aspects of the PSPs can become important for the spatial or temporal signal integration depending on the localization of the spine on the dendritic tree and the function of the cell. To condense information from the potential curves, we defined three characteristic electrical properties: the peak-value V_{peak}, area A, peak-time t_{peak}. The peak-value is important to stimulate a local action potential. The area is proportional to the overall impact and the peak-time is important if coincidence detection is in focus of interest.

3.2 Systematic variation of spine shape

Each of the four geometric parameters was varied in 10 steps resulting in 10000 different combinations. Fig. 3 summarizes the results for peak values and peak-time of PSP of all geometric combinations.

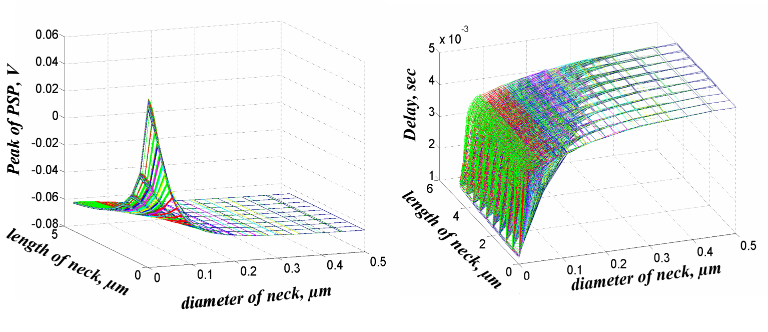

Fig. 3 Summary of the characteristic values by systematic variation of geometry

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Each combination of length and diameter for a spine head is represented by one plane in the figure. The shape of the spine head had no large effect to signal transmission, but it allows small variations without changing neck geometry, a mechanism which might be relevant for learning processes. Quite remarkably, a variety of possible combinations of shape parameters result in nearly identical electrical behaviors. The simulation results reveal that a spine is capable of adjusting the incoming energy per spike (area *A*), that can be considered as part of the synaptic weight. Additionally, the spine can modulate the shape of a PSP to achieve a precise adjustment of coincidence detection in a temporal integration mode by setting the delay (peak-time). And it can adjust its peak potential to reach the threshold to trigger a local action potential.

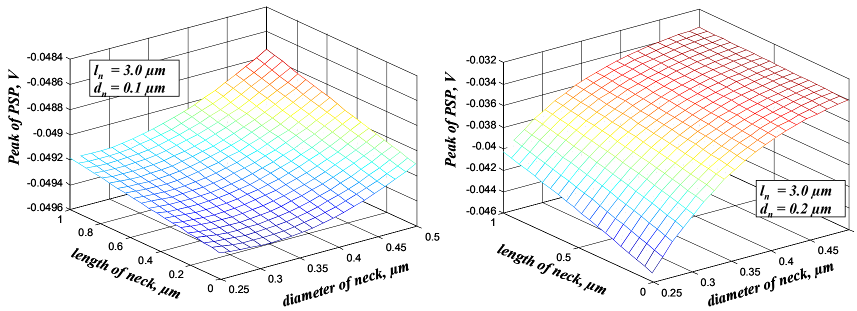

Fig. 4 Change of peak-size by variations of head shape with constant neck value

For further detailed analysis, the calculation of electrical values from geometric values can be approximated to reduce the high numerical effort for compartment simulation. A multilayer perceptron (4-10-10-3) is trained by a standard backpropagation algorithm and by the calculated data from compartment simulation with a sufficiently small error. This approximation allows to calculate fast projections of the four-dimensional parameter space with high resolution (see Fig. 4) and to increase the speed for the analyses of iterative learning mechanism (see next section).

3.3 Adaptation of electrical properties

Is it possible for a spine to obtain specific new electrical properties by changing its geometry? Could this mechanisms play a role in learning events, e.g. learning a new behavior in the real brain? Instead of searching for specific parameter combinations in our database we focused on mechanisms which are involved in the transition from one type of electrical behavior to another type. In order to keep the conditions as close as possible to “real” biology we must consider that spines have neither a memory to perform a global search nor do they receive detailed feedback signals. However, it is known, that spines undergo rapid dynamic changes of shape by fast twitching movements [12] with decreasing amplitudes over time [3]. The statistics of this rapid twitching is not known. If we assume that this motility reflect a mechanism to adapt spine geometry, we postulate that these twitches may not occur completely at random. All we need is a slightly higher likelihood to change the shape in the direction of the ‘target’ properties that are reached iteratively. A mechanism which is very similar to that has to be described as ‘simulated annealing’ (SA) [13]. SA is used in image proc-

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essing to adapt geometric models to complex noisy images [14] and it requires only alterations in the quality as feedback signal but no additional internal memory. SA works simple: all free (here the four geometric) parameters twitch around a center value randomly with a defined maximum amplitude. If a new parameter combination offers a better quality the twitching stops and the new combination is used as the center value. Otherwise, it twitches back most time, but stay sometimes with small probability to have a changes to escape local minima. Maximum amplitude of twitching decreases over time to 'freeze' the final properties.
To tryout the algorithm in simulation we selected a starting geometry (l_n, d_n, l_h, d_h) of spine (spine 1 in Fig. 2) with corresponding electrical properties (V_{peak}, A, t_{peak}). The goal is to reach different electric properties (V'_{peak}, A', t'_{peak}), which were obtained from another spine of different geometry (spine 3 in Fig. 2). In this way we are sure that there is a possible solution. The actual quality of a combination of geometric parameters was determined by the weighted sum square error of the electrical properties calculated by the ANNs. The importance of each electrical property can be modified by the weights depending on the task of the spine (temporal vs. spatial integration). The maximum amplitude of twitching is set individually for each geometric parameter to include the cost or energy of changing this geometric parameter.

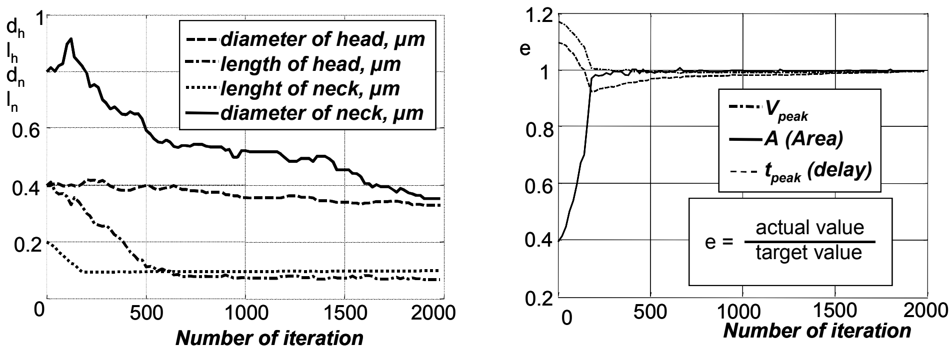

Fig. 5 Changing geometric and electric values by simulated annealing

Fig. 5 shows a progress of learning in 2000 iterations. The resulting PSP (spine 3 in Fig. 2) comes very close to the target behavior. The target behavior was obtained in all tests. Despite of reaching the electrical target properties the adjustment of geometric properties by this learning mechanism depends on the initial geometry, the parameters of the SA algorithm and also on the statistics of the twitching. Experiments are underway in which more than one spine is analyzed, where the interaction between spines has to be taken under consideration.

4. Discussion and Conclusion

The information processing in dendrites and spines using nonlinear temporal and spatial integration of input signals is highly complex and depends on many parameters. One of them is the geometry of the spines. Our results are in line with our hypothesis that already a single spine is able to modulate the signal transmission by

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changing its shape, i.e. it can learn a new behavior. There is a crossover from one to any other possible electrical property which can be found by simple mechanisms like simulated annealing. Biological mechanisms may use a change in statistics of twitching parameters. If twitching is considered as added noise with zero sum over time. A feedback signal may depress this noise for a short time. This is sufficient to change the overall mean value in right direction. Our results may provide one further step to understand the information processing inside a single synapse, and also of an entire neuron in more detail. Moreover, this theoretical approach may help to design new learning rules for artificial (and perhaps also natural) neural networks. However, it has to be pointed out that geometrical changes of spines are only one aspect in this highly complex game. Changing of dendrite geometry, spine frequency and biochemical changes in synapses and membrane have also an important influence and must be considered in this context.

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