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Information theoretic optimization of cochlear implant electrode usage probabilities

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Abstract— **Cochlear implants are neural prostheses that can restore hearing. Contemporary cochlear implant devices consist of up to 22 electrodes. An open question for future cochlear implants is whether new electrode designs that enable less current spread may provide improved hearing performance through more precise control of neural activation, more electrodes, or more precise positioning. Here we use a recently proposed information theoretic model for the electro-neural interface that enables estimates to be made of the optimal number of electrodes for different amounts of current spread. We apply information theoretic approaches for finding the channel capacity in the model to enable estimates of optimal electrode usage probabilities and positions. We also compare the performance in the model when auditory nerve fibers are assumed to be heterogenous, with a random distribution of firing thresholds and relative spreads, versus an assumption that they are all identical.**

I. INTRODUCTION AND BACKGROUND

Cochlear implants [1], [2] are biomedical neural prostheses that can help people with hearing loss caused by loss of inner hair cells in the cochlea (inner ear). In a healthy ear, inner hair cells convert sounds into electrical pulses called action potentials in fibers of the auditory nerve. These action potentials propagate to the brain where they are processed and perceived as sound. The function of a cochlear implant is to replace the missing inner hair cells, which is achieved by an electrode array that is implanted in the inner ear. Sound is captured by a microphone and converted into electrical signals in different frequency bands, which then drive the electrodes of the array to directly stimulate the auditory nerve [3].

Contemporary cochlear implants use arrays of up to 22 electrodes. More electrodes than this do not improve hearing performance. The primary limiting factor is thought to be current spread [4], which causes electrodes that are close together to stimulate similar groups of auditory nerve fibers. Within the cochlea, the electrodes cannot be positioned any closer to the auditory nerve, so an alternative method for minimizing the problems of current spread is through focussed stimulation, more precise positioning of electrodes, or optimizing electrode usage probabilities.

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Previous work has already developed an information theoretic modeling framework for estimating the optimal number of electrodes in cochlear implants from an information theoretic perspective [5]. This approach relies on a model of stochastic action potential generation, and the interface between the array of electrodes and the auditory nerve is conceptualized as a discrete memoryless channel (DMC). It enables numerical calculations of the mutual information between an input random variable (choice of electrodes) and an output random variable (defined as a function of the active nerve fibers in response to an electrode choice).

However, in [5], electrodes are assumed to be uniformly distributed along the array and used with identical probabilities. To determine whether changing these two assumptions can significantly improve performance in the model, here we aim to find the optimal usage probability of each electrode. We study this in order to see if attempting to optimize electrode usage probabilities and/or placements might be a feasible way to improve the performance of cochlear implants.

A. *Overview of modeling framework*

The model proposed in [5] has five individual components, each of which can be individually improved or adapted. For example, components 2 or 3 can be adapted by applying realistic finite element method models [6]. The five components in [5] are:

1) geometry of fiber and electrode locations;
2) mechanisms of stochastic action potential generation in fibers of the auditory nerve;
3) current spread from each electrode;
4) dependence of loudness perception on overall auditory nerve activity;
5) information theoretic modeling of place discrimination.

In [5], we extended a simple existing stochastic model of electrically evoked auditory nerve activity [7], and estimated the mutual information between a choice of electrode, and the output of our place discrimination model. Here, we study channel capacity, which is the maximum mutual information between the input random variable, $X_e(j), j = 1, \dots, M$, and an output random variable Z. The input $X_e(j)$ describes the normalized location of electrode j along the array, M is the number of electrodes, and Z is defined as a function of active nerve fibers. The mutual information is defined as:

$$I(X_e; Z) = -\sum_{i=1}^{M+1} P_Z(i)\log_2(P_Z(i)) + \sum_{j=1}^{M} P_{X_e}(j)\sum_{i=1}^{M+1} P_{Z|X_e}(i|x_{e,j})\log_2(P_{Z|X_e}(i|x_{e,j})), \quad (1)$$

where $P_Z(i) = \sum_{j=1}^{M} P_{X_e}(j)P_{Z|X_e}(i|x_{e,j}) \quad \forall i = 1,\ldots,M+1$. A more detailed definition of Z and the $(M+1)$–th output state can be found in [5].

Apart from aiming to maximize mutual information by varying electrode usage probabilities, we otherwise strictly follow the same assumptions and parameters of [5], except where mentioned. In that work, the mutual information was computed for assumed numbers of total electrodes between 2 and 45. In this way, the optimal number of electrodes is that which achieves the maximum mutual information. In a DMC, if the input probabilities can vary, the channel capacity can increase, and finding channel capacity for a given number of electrodes is clearly an optimization problem. We discuss methods for carrying out this optimization in Section II. First, however, we discuss the stochastic action potential model.

B. Random fibers

In our modeling framework, as introduced in [5], a Bernoulli random variable, $Y_i \in \{0, 1\}$, denotes whether fiber i produces an action potential in response to current $C_{f,i}$, or not. $Y_i = 1$ is the case that fiber i generated an action potential and $Y_i = 0$ otherwise. The probability that $Y_i = 1$ given the current that stimulates it is $C_{f,i}$ is assumed to be described by

$$P_s(C_{f,i}) := 0.5\left(1 + \operatorname{erf}\left(\frac{C_{f,i} - \theta_i}{\sqrt{2}\sigma_i}\right)\right), \quad (2)$$

where $C_{f,i}$ is the current in amperes at the location of fiber i, θ_i denotes the current that produces an action potential with the probability of one half, and σ_i is given by $\sigma_i = (\mathrm{RS})\theta_i$. RS is the relative spread of a fiber's firing response as in [8], [9].

We study two cases. In the first case, all fibers have identical thresholds and relative spreads. In the second case, which we call 'Random Fibers', the auditory nerve fibers are assumed to have thresholds randomly chosen from a uniform distribution on $[-5 + E(\theta), 5 + E(\theta)]$ on a decibel scale. Also, relative spreads are randomly chosen from a normal distribution with a standard deviation of 0.06 and a mean that is obtained from the equation of $E[RS]$. These choices are the same as in [7]. As a consequence of introducing this heterogeneity, the mutual information and the optimal input distribution at channel capacity may be different for independent trials in which the parameters are different, just as they might be in different cochlear implant users.

II. FINDING CHANNEL CAPACITY AND CAPACITY-ACHIEVING INPUT PROBABILITIES

The classical Blahut-Arimoto algorithm [10] is a widely used technique for numerically obtaining channel capacity for a given DMC. This is an iterative algorithm that can converge to a solution for channel capacity for any given DMC by alternately modifying the input and the output distribution. Since it is simple and well-known, the Blahut-Arimoto algorithm has been widely used in practice. A more efficient algorithm called convex optimization [11] is also applicable to channel capacity problems. Thus, the channel capacity problem can be solved directly by either the Blahut-Arimoto algorithm or convex optimization. In this paper, both Blahut-Arimoto algorithm and convex optimization are used for calculating channel capacity.

III. RESULTS

In this section, we first present and discuss results obtained via numerical evaluation of channel capacity and capacity-achieving input distribution as a function of array-to-nerve distance r and number of electrodes M. Then we investigate to what extent the randomness of fibers influences the optimal number of electrodes. All parameters are the same as in [5]; the major difference is that we compute mutual information and optimal number of electrodes after optimizing input distribution, and use the mutual information achieved by uniformly distributed inputs and the corresponding optimal number of electrodes as comparison. Following [5], the distance between the electrode array and auditory nerve fibers is assumed to be $r \in [0, 2]$ mm, and the total number of fibers is assumed to be $N = 10000$. In this paper, we only consider the case of maximum current $C_{\max}$ where the mean spike count E is calculated as $E[Y|C_{\max}(r)] = 0.1N$ [12]. Here, maximum current level is defined as the value of current that produces neural activity with perceived loudness at a maximum "comfortable level". Because acceptable performance of cochlear implants generally results from stimulation of electrodes at current levels towards the top of the dynamic range (i.e., close to $C_{\max}$), our results in this paper are sufficient to illustrate how the electrode usage probabilities influence mutual information and the corresponding number of electrodes.

A. Mutual information and corresponding input distribution

We computed the mutual information as a function of $r \in [0, 2]$ mm and for all $M = 1,\ldots,50$. Note that the mutual information is directly a function of current at each fiber which is as a function of r [5]. Here, we fixed the positions of the electrodes, so the channel capacity (maximum mutual information) could be easily found by applying the Blahut-Arimoto algorithm or convex optimization. The mutual information and corresponding input distribution for uniformly distributed inputs and non-uniformly distributed inputs are shown in Fig. 1. In the figures of this paper, BA refers to the Blahut-Arimoto algorithm. Since the Blahut-Arimoto algorithm and convex optimization lead to the same channel capacities for all electrode array sizes, we only present the results obtained by the Blahut-Arimoto algorithm.

We also computed channel capacity-achieving input probability distributions for some specific cases of M. Fig. 2

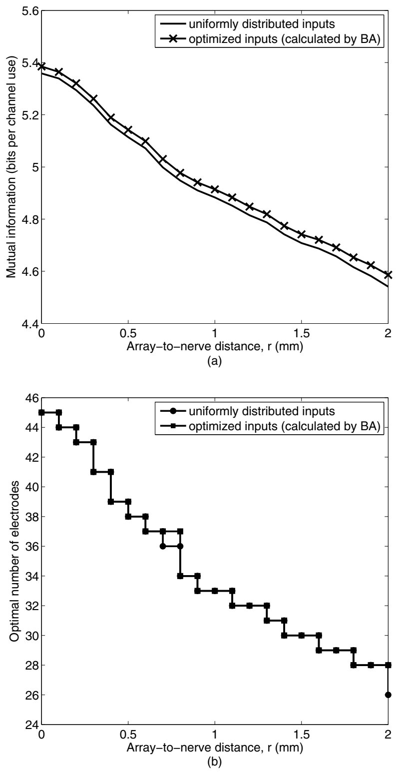

Fig. 1. Comparison of uniformly distributed input probabilities and optimized input probabilities. Mutual information achieved by optimal number of electrodes (a) and optimal number of electrodes (b) as a function of array-to-nerve distance r. Optimization via Blahut-Arimoto algorithm and verified (not shown) by convex optimization.

shows two example optimal input distributions for $M = 6$ and $M = 26$. The resultant probability for each point in the distribution is equivalent to the optimal usage probability of an electrode located at that point. At this stage, we only consider $r = 2$ mm, since in reality the distance between the electrode array and auditory nerve fibres is usually no less than 2 mm. As expected, we found that the input distributions obtained by the Blahut-Arimoto algorithm and convex optimization were identical even when we varied the number of electrodes. Note that the channel capacity is achieved by non-uniformly distributed electrode usage probabilities only when the number of electrodes is large, i.e. comparable to the optimal number of electrodes achieved when the probabilities are not optimized. Channel capacity can be achieved by uniformly distributed probabilities when the number of electrodes is small.

B. The impact of randomly chosen fiber parameters on the optimal number of electrodes

We estimated the impact of randomly setting fiber thresholds and relative spreads (see Section I.B) on the optimal number of electrodes by computing the mean, maximum, and minimum of the optimal number of electrodes from 20 independent trials. The results in Fig. 3 show the range of the optimal number of electrodes for $r \in [0, 2]$. We found that the randomness of the fibers indeed influences the optimal

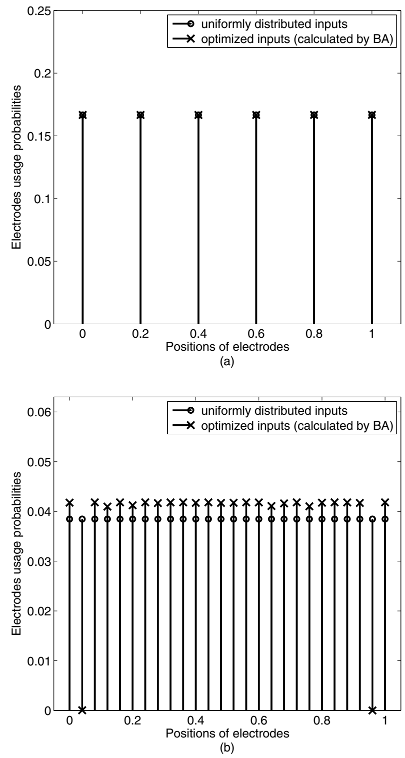

Fig. 2. Channel capacity-achieving input distributions. Capacity-achieving input distributions calculated via the Blahut-Arimoto algorithm and verified (not shown) by convex optimization. Two cases are shown: (a) $M = 6$, (b) $M = 26$.

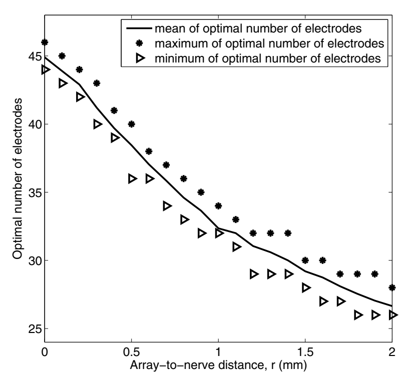

Fig. 3. Comparison of mean, maximum, and minimum of optimal number of electrodes for $C_{\max}$ as a function of array-to-nerve distance r, from 20 trials of randomly chosen fibers.

number of electrodes to some extent. However, the range of optimal number of electrodes is no larger than 3 electrodes for all values of r.

IV. DISCUSSION

A. Channel capacity-achieving input distribution

No obvious difference in optimal number of electrodes was found between uniformly distributed electrode probabilities and optimized electrode probabilities. However, the mutual information that corresponds to the optimal number of electrodes shows a slight increase for the whole range of the array-to-nerve distance, after optimization. Further, we found that the capacity-achieving input distributions show significant differences only for the cases where the electrode array sizes approach or exceed the optimal number of electrodes. This phenomenon can be related to how we denote the ambiguity output states in this modeling framework. An ambiguity output state is defined as two or more fiber partitions generating action potential count difference smaller than a constant D [5]. The number of fiber partitions is the same as the number of electrodes. Thus, the ambiguity state is more likely to occur when the number of electrodes is increased, which can be expected in real auditory nerve fibers due to current spread. The result in Fig 2(b) shows that the input probabilities fall to approximately zero at the second electrode and the penultimate electrode. The 50% less fibers in the first partition and in the last partition is caused by the way we define the partitions of fibers. As a consequence, the ambiguity state is far more likely to appear when the stimulated electrode is close to the first two partitions or the last two partitions.

The results here illustrate that the method of defining the output states will have an influence on the performance of our modeling framework. Thus, if we change the way that we define the channel's output states (corresponding to a changed conceptual model about how the brain interprets activity in the auditory nerve), an improvement of this modeling framework could be expected. Furthermore, varying the positions of electrodes can increase the channel capacity and vary capacity-achieving distribution, which can be an alternative way for estimating the optimal placements and usage probabilities of electrodes.

B. How randomness of fibers influence the optimal number of electrodes

We introduced random fibers into our modeling framework, then we calculated the optimal number of electrodes using $C_{\max}$. No more than a range of 3 electrodes for the optimal number of electrodes were observed for any value of r. We conclude that randomness of fibers does not have a large effect upon the optimal number of electrodes estimated in the model. The mean optimal number of electrodes decreases monotonically with the increasing of array-to-nerve distance, which exactly follows the theory and our expectation. The result suggests that the same design of electrode array might be used for almost all patients, as the random fibers do not greatly influence the optimal number of electrodes.

However, here we present results only for 10000 nerve fibers in the model, and all fibers are uniformly located along the electrode array. In future work, we plan to study variations of the auditory nerve fiber survival rate and fiber locations in the model.

In general, there remain a number of aspects that can be improved and made more realistic without altering the basic framework and approach. For example, we define output states based on electrode array sizes and locations of electrodes, which forces us to fix the number and positions of electrodes before we optimize the electrode usage probabilities. An improved design of output states might enable us to remove assumptions about the number and locations of electrodes, and allow the information theoretic optimization to freely find the optimal values of these parameters. When the positions can vary, channel capacity can increase, and the optimization problem in standard form is non-convex. However, the problem can be converted to a convex one [13], and using this approach allows us to relate the capacity-achieving input positions to the optimal positions of electrodes. Also, a more realistic spiral model for the cochlea and electrode array was studied in [14]. Comparing optimized, non-uniformly distributed electrodes in this three-dimensional spiral model with the original model, which used a linear geometry, can be other valuable future work.

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