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PRESELECTION OF NEUROSTIMULATION WAVEFORMS FOR VISUAL PROSTHESES USING GENETIC ALGORITHMS

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Abstract: Among the variety of approaches for developing therapies for the blind, electrical neurostimulation of the visual pathways seems to be a promising choice. Delivering bi-phasic bioelectric pulses to the nerves implies the selection of values for a number of parameters within a wide range. This needs to be done for every implanted electrode, and for every patient. Nowadays, electrode arrays can include up to one hundred channels, and we expect to raise to thousands of them in a near future. This unavoidable task becomes extremely time-consuming both for the researcher and for the patient. Therefore, in order to reduce the number of tests to be carried out in vivo, we propose the use of multi-objective genetic algorithms that can provide a limited set of candidate waveforms to be tried.

1 INTRODUCTION

According to estimations by the World Health Organization (WHO, 2005), 45 million people are legally blind, and more than 135 million persons suffer from low vision. The number of patients losing their visual function is expected to rise in the next years, as many of the illnesses causing blindness are related to aging.

Whenever a person gets blind, severe limitations in a variety of aspects of his or her life arise. The patient finds a number of handicaps in daily activity, labor, autonomy, social interaction, etc. Additionally, blindness imposes high costs to public health administrations.

The term blindness has a functional meaning. However, a wide variety of traumas and illnesses can be behind this condition: age-related macular degeneration (AMD), diabetic retinopathy, retinitis pigmentosa (RP), cataracts, accidents, etc.

The plethora of resources under research for curing blindness is even more varied than the illnesses behind it. Research groups are trying to find treatments for visual deprivation from different perspectives: pharmacology, surgery, gene therapy, or even electrical neurostimulation.

This paper presents an approach to obtain a reduced set of stimulation parameters in order to limit the range of possible combinations of possible values for electrical neurostimulation. The optimization of the parameters is done by means of a multiobjective genetic algorithm which is able to find a balance between the different solutions.

2 VISUAL NEUROPROSTHESES FOR BLINDNESS

This last bioengineering therapeutic research line tries to restore a rudimentary, but functional form of visual perception, by artificially stimulating part of the valid remaining neural tissue in the visual pathway.

In this line, several research projects for creating a visual neuroprosthesis for the blind are currently under development. Thus, we can mention retinal implants (Humayun, 2003), optic nerve implants (Veraart, 1998), and cortical implants (Troyk, 2003; Fernández et al., 2005a). All of them try to elicit visual perceptions by electrically inducing the activation of nerve cells in the visual pathway.

Some encouraging results from primitive attempts can be found in the literature, demonstrating the proof of concept for visual neuroprosthetic implants (Dobelle, 2000; Schmidt et al., 1996). In these cases, patients related the perception of visual sensations when an electrical pulse was delivered to the implant.

However, a long list of issues needs to be addressed in order to have a fully usable implant for the blind: biocompatibility, information processing, portability, and reliability (Normann et al., 2009). One of the challenges in these neurostimulation systems is finding adequate values for a number of parameters of the stimulation waveform.

We present in this paper an approach to find a set of candidate waveforms using a multiobjective genetic algorithm. In this way it is possible to find a balance between the different values to be optimized.

Then, the number of trials with patients in clinical research can be significantly reduced, as only a reduced set of specific neurostimulation waveforms need to be tested in vivo.

3 ELECTRICAL NEURO-STIMULATION WAVEFORMS

In order to activate a neuron in a biological tissue, an action potential can be generated by putting an electrode in the neighborhood of the cell, and delivering electrical charges in the medium (charge injection), or using the same electrode to create an electrical field that elicits the re-distribution of electrical charges in the surroundings. The effect, under adequate conditions, is the generation of a pulse along the axon of the neuron, known as action potential. This pulse can be transmitted to the rest of neurons in the visual pathway, activating a percept in the visual field of the patient.

Traditionally, neurostimulation pulses are biphasic square waveforms. A negative current at the beginning induces the effect of the action potential (”cathodic-first stimulation”), while the positive counter-phase restores electrochemically the neighborhood of the active tip of the electrode. This way, the amount of charge after the pulse is delivered remains balanced.

Usually, a train of biphasic pulses is required to elicit a visual percept or ”phosphene” (a perception similar to a star in the sky).

The set of values for getting a patient seeing a phosphene is unknown, and needs to be determined experimentally. Moreover, these values can be different for every electrode in an implant, and for every implanted patient. This means, that testing all possible combinations of waveform parameter values, for every electrode in an implant of 100 or even more electrodes can take an excessive amount of time.

The set of parameters of the stimulation waveform are the following:

- Current: amplitude of the negative and positive phases).
- PD: pulse duration (pulse width in the positive or negative phase).
- IPHI: inter-phase interval (time between negative an positive phases).
- IPI: inter-pulse interval (time between two consecutive biphasic pulses).
- NPulses: number of pulses in a train.

Time parameters are usually expressed in microseconds, and current is expressed in microamperes.

Our objective is to minimize the amount of charge injected in the neural tissue (to avoid undesirable harmful effects), which should be over an unknown threshold in order to elicit a phosphene. Additionally, we want to maximize the duration of the phosphene (”onset”), and the brightness of the percept.

In order to enhance the design of a visual prosthesis (Fernández et al., 2005b), we have developed a simulator of visual prostheses, based on limited results of real human implants, from which the rules for generating the outputs have been extracted.

4 GENETIC ALGORITHMS APPLIED TO NEUROSTIMULATION OPTIMIZATION

Genetic algorithms (GAs) are general purpose search algorithms which use the principles inspired by natural genetics to evolve problem solutions (Golberg, 1989). These algorithms have been succesfully applied to a wide range of real-world problems (Guillen et al., 2009; Casillas and Carse, 2009; Cordón et al., 2007; Guillén et al., 2006; Isibuchi, 2007) and are well known in the computer science field.

A GA defines an initial population of individuals, each individual encodes a solution to the problem. The algorithm iterates until a stop criterium is reached, the sequence of steps that is followed on each iteration is:

1. evaluate each individual

2. select individuals to be crossed
3. apply the crossover operators to generate the offsprings
4. select which offsprings and ancestors will form the next population
5. apply mutation

The idea underneath these algorithms is that if two good solutions are combined together, the resulting solutions could be better. The literature regarding GAs presents a large number of papers performing studies to the different parameters and proposing new crossover, mutation, selection policies, etc. Among this vast variety of GAs, there is a special kind known as MultiObjective Genetic Algorithms (MOGA). The main feature of these is that they do not consider a unique value to determine the quality of a solution (individual) but use a vector of values. Thus, for some individuals, it is not possible to say that one individual is better than the other. A Pareto front is a set of solutions where each solution is not better than the others.

In a formal way, a multi-objective optimization problem can be defined in the following way:$min/max\overrightarrow{y} = f(\overrightarrow{x}) = f_1(\overrightarrow{x}), f_2(\overrightarrow{x}), \cdots, f_n(\overrightarrow{x})$ where $\overrightarrow{x} = (x_1, x_2, \cdots, x_m)$ is a solution and $\overrightarrow{y} = (y_1, y_2, \cdots, y_n)$ is the objective vector (a tuple with n objectives). The aim of any MOGA is to find all the solutions for which the corresponding fitness value can not be improved in a dimension without degrading another. Therefore, these algorithms can be applied to set some guidelines when adjusting the electrodes for neuroestimulation, reducing the number of trials and saving time and effort to both pacients and researchers.

4.1 Non-dominated Sorting GA-II

One of the most famous MOGAs is the Non-dominated Sorting GA-II (NSGA2) (Deb et al., 2002). This algorithm has been widely used in many applications providing satisfactory results.

The main characteristic of this algorithm is the way in which the population of the next generation is obtained. It performs an efficient sorting of the original population and the offsprings generated, obtaining the different sub Paretos and adding them into the new population until it is completed.

4.1.1 Encoding a Solution

The first step that should be done when applying a GA is the determination of how an individual encodes a solution. For the problem tackled in this paper, an individual consits in a vector of real values where each gene encondes the three parameters to be optimized.

Figure 1 shows a parameter configuration and how this is encoded in an individual (Cu=20; PD=60; IPHI=180; IPI=90; NPulses=84).

Table 1: Representation of a chromosome.

Genotype				
Cu	*PD*	*IPHI*	*IPI*	*NPulses*
20	60	180	90	84

4.1.2 Genetic Operators

In this work the standard genetic operators have been used: Tournament Selection (Miller and Goldberg, 1995), BLX-α ($\alpha = 0.3$) and Uniform Mutation. For a real coded genetic algorithm, this type of operators have shown an adequate performance reaching a balance between the exploration of the solution space and the explotation of the good values intervals.

5 EXPERIMENTS

This section presents the results provided by the algorithm for a simulated patient. The model that has to be optimized was described previously, therefore, the output of the implemented MOGA is a vector of three values (Q,*Brightness*,*Onset*).

There is a wide research on how these parameters could be tuned, nonetheless, those heuristic can be always replaced by a manual adjustment based on a set of experiments. Thus, the given values were the most adequate after several tests. Due to the non-deterministic nature of GAs, the algorithm was executed 10 times providing robust results with a few variation in the results.

In this study the average values of the ten experiments are shown in Table 2 for the objectives considered: Q, *Brightness* and *onSet*.

Table 2: Average values results of the objectives considered in the algorithm.

Objective	*Value*
Q	1.250 nC
Brightness	128 $\in$ [0,255]
onSet	64800 μs

As the results showed, the ouput of the algorithm sets the current in a fixed value, obtaining a wider variety of solutions only for the other two objectives.

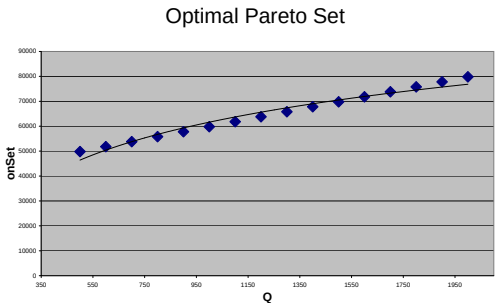

Figure 1: Final Pareto obtained by the algorithm.(Units: onSet is expressed in microseconds, and Q is expressed in pC).

6 CONCLUSIONS

The tunning of stimulation parameters for visual neuroprostheses still remains as one of the most troublesome issues to be faced due to the large number of parameters and the wide range of values. This paper has presented an application of one of the most famous optimization tools to this problem such as Genetic Algorithms. These techniques allow the researchers to obtain a reduced set of possible solutions so the range of recommended values to be tested in vivo is significantly reduced. For the concrete case described in the paper, from the 15*15*15*15*100*255=1,290,937,500 possible solutions, a reduced subset of 16 solutions was obtained. The implementations were tested over a simulation software providing satisfactory results, showing how useful is to apply these techniques in order to improve the adjustment of the neuroprostheses.

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