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Optimization of kinetic energy harvesters design for fully implantable cochlear implants

A. Sudano, D. Accoto, *Member, IEEE*, M. T. Francomano, F. Salvinelli,
E. Guglielmelli, *Senior Member, IEEE*

Abstract—**Fully implantable Cochlear Implants (CIs) would represent a tremendous advancement in terms of quality of life, comfort and cosmetics, for patients with profound sensorineural deafness. One of the main challenges involved in the development of such implants consists of finding a power supply means which does not require recharging. To this aim an inertial Energy Harvester (EH), exploiting the kinetic energy produced by vertical movements of the head during walking, has been investigated. Compared to existing devices, the EH needs to exploit very low frequency vibrations (<2.5 Hz) with small amplitude (<9 m/s^2). In order to maximize the power transduced, an optimization method has been developed, which is the objective of this paper. The method consists in calculating the dynamical behavior of the EH using discrete transforms of experimentally measured acceleration profiles. It is shown that the quick integration of the second order dynamical equation allows the use of computationally intensive optimization techniques, such as Genetic Algorithms (GAs). The robustness of the solution is also evaluated.**

I. Introduction

Cochlear implants (CIs) are widely used to directly stimulate auditory nerves to restore compromised functionality in profound sensorineural hearing loss [1, 2]. In this framework, fully implantable CIs could be a novel solution for improving users' quality of life in terms of comfort and cosmetics. Despite of their expected advantages, their actual development is hindered. One of the major limitations is due to the lack of an implantable stand-alone power supply system. Indeed, existing devices require rechargeable batteries to be mounted on the scalp, connected to a system, which is inductively coupled to an implanted receiving coil [3].

Energy harvesters (EHs), i.e. compact devices (from 10^{-1} to 10^5 mm^3) able to convert mechanical energy available in the environment surrounding the CI into electrical energy [4], seem to be one of the most suitable alternatives to existing powering techniques.

A wide variety of EHs [5] has been developed in recent years, transducing into electricity several forms of energy [6] (e.g. thermal, mechanical, electromagnetic, metabolic). However, no existing EH can be used for powering autonomous CIs, because of the low power density, excessive size, weight and mechanical noise [7]. Considering all these issues, kinetic energy harvesters, which transduce kinetic energy into electric energy, look quite appealing for the specific application [4] in terms of power density [8]. Physical models of kinetic EHs [8] (piezoelectric, electrostatic and electromagnetic) have been developed to allow the optimization of mechanical, electrical and magnetic parameters. Optimization strategies may employ analytical [9], lumped parameters [10, 11] or FEM [12] models.

Compared to other works, the main novelty presented in this paper consists in performing a search for optimal parameters using Genetic Algorithms (GAs) while working with real head acceleration measurements. Given the large amount of calculations required by genetic algorithms, a mathematical method is presented, based on Discrete Fourier Transform (DFT), which allows to significantly reduce simulation time, if compared to standard numerical integration methods (e.g. Runge-Kutta 4-5), with a negligible loss of spectral content.

The second order mechanical system, whose parameters have been optimized, is described in Sec. II. Preliminary results are shown in Sec. III, while Sec. IV is dedicated to conclusions and future work.

II. Methods

A. Mechanical model

The energy source for the EH is the kinetic energy associated with head movements. In this framework, a preliminary simplified mechanical model has been performed considering only vertical movements of the head during walk, which put in motion an oscillating mass (m), similarly to what was reported in [4]. Figure 1 depicts the schematic of the mechanical subsystem of the EH. The mass is coupled to a flywheel (moment of inertia: I), e.g. by means of a pinion-rack mechanism or equivalent, so that the system has one degree of freedom, e.g. the vertical displacement δ. A torsion spring (k) and a torsion damper (c) are mounted between the flywheel and the frame. If the pinion, fixed to the flywheel, has a radius r, then a translation δ of the inertial mass (m) with respect to the frame causes a rotation θ of the flywheel, according to $\vartheta = \tau\delta$, where$\tau = 1/r$ is the transmission ratio. The

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A. Sudano, D. Accoto, M. T. Francomano, E. Guglielmelli are with the Biomedical Robotics and Biomicrosystems Lab, Università Campus Bio-Medico di Roma, Italy (phone: +3906225419610; e-mail: d.accoto@unicampus.it)

F. Salvinelli is with the Unit of Otolaryngology, Università Campus Bio-Medico di Roma, Italy (f.salvinelli@unicampus.it).

dynamics of the system is described by:

$$(I\tau^2 + m)\ddot{\delta} + c\tau^2\dot{\delta} + k\tau^2\delta = k\theta_k + m(a(t) - g) \quad (1)$$

where θ_k is the rest angular position of the torsion spring, $a(t)$ is the (absolute) head acceleration and g is the gravitational acceleration ($g = 9.81\ m/s^2$).

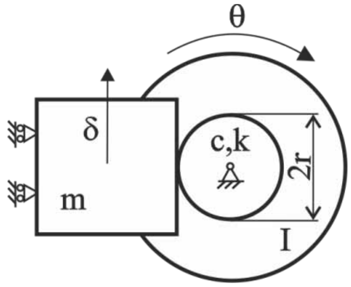

Fig. 1. Schematic of the EH mechanical subsystem. The oscillating mass (m) causes a rotation of the flywheel ($\theta = \delta\tau$) hinged to the frame and connected to a torsion spring (k) and a torsion damper (c).

By introducing the following parameters:

$$\begin{cases} M = I\,\tau^2 + m \\ C = c\tau^2 \\ K = k\tau^2 \end{cases} \quad (2)$$

and setting $\theta_k = mg/k$, so that when $\theta = 0$ the spring is balancing the effect of gravity, equation (1) simplifies into:

$$M\ddot{\delta} + C\dot{\delta} + K\delta = ma(t) \quad (3)$$

The equivalent damping coefficient C comprises the actual mechanical damping, C_m, and a factor, C_e, which accounts for the energy not dissipated but extracted on purpose from the mechanical system to be converted into electric energy. In short:

$$C = C_m + C_e \quad (4)$$

This choice implicitly assumes that the extraction of electric energy causes an equivalent braking torque $C_e\dot{\delta}$. Such assumption correctly applies, for instance, to electromagnetic transducers based on Faraday-Lenz law.
In general, C_e depends on the actual transduction technology and power electronics (e.g. voltage boosters, converters, etc.) [13] and it might introduce mathematical non-linearities. In what follows, for simplicity sake, C_e is assumed to be independent from the linear displacement δ, so that the model retains its linearity. Under these hypotheses, the average electrical power P_{av} is given by:

$$P_{av} = \frac{1}{T}\int_0^T C_e\dot{\delta}^2\,dt \quad (5)$$

where T is the integration period.

B. Model bandlimiting and discretization

The optimization procedure is based on experimental head acceleration data collected using a magneto-inertial sensor *XsensMTx* [14] according to the protocol described in [4]. Differently from [4], collected data refer to 5 healthy subjects (age: 23±1), the sampling frequency has been increased to 200Hz, and the recording time has been extended to 160s.

As already discussed in [4], each subject has its own walking style, characterized by a specific cadence, stride and head acceleration spectrum. Given the objective of this paper, i.e. presenting a methodology for optimizing the mechanical parameters of an energy harvester, an acceleration head profile has been randomly selected among the five recorded ones. This causes no generality loss, because the same procedure can be applied to any other head acceleration profile, e.g. in order to find the optimal mechanical parameters customized for a *specific* patient. Nonetheless, in order to verify that the found solution, in terms of optimized M, C, K, m, is not too sensitive to the specific acceleration profile used as input, simulations have been performed with the other four acceleration profiles, determining the corresponding average power (Sec. III).

In order to analyze the linear system (3) in the frequency domain, the Discrete Fourier Transform (DFT) is used.
The transfer function associated to (3) in the frequency domain is:

$$H(\omega) = \frac{1}{-\omega^2 M + j\omega C + K} \quad (6)$$

Since the input signal has a limited bandwidth, also (6) can be correspondingly bandlimited and consequently time sampled:

$$\hat{H}(\omega) = \frac{1}{T_s}\sum_{k=-\infty}^{+\infty} H_{lb}\left(\omega - 2\pi\frac{k}{T_s}\right) \quad (7)$$

where T_s is the sampling period and $H_{lb}(\omega)$ is the bandlimited transfer function. Finally the DFT of the system, for an odd number of samples N, is:

$$\hat{H}[k] = \begin{cases} \hat{H}\left(\frac{2\pi\,k}{NT_s}\right) k = 0, \dots, \frac{N-1}{2} \\ \hat{H}^*\left(2\pi\frac{N-k}{NT_s}\right)\ k = \frac{N+1}{2}, \dots, N-1 \end{cases} \quad (8)$$

The output of the system in the discrete frequency domain is:

$$\Delta[k] = \hat{H}[k] \cdot mA[k] \qquad k = 0, \dots, N-1 \quad (9)$$

which, by means of the Inverse Discrete Fourier Transform

(IDFT), becomes, in the discrete time domain, the output $\delta[n]$.

C. Optimization

The optimal model parameters (*M*, *C*, *K*, *m*) have to be identified in order to maximize the generated electric power (5). To this aim, an optimization methodology, based on a Genetic Algorithm [15], has been devised.

Because of the desired implantability of the EH, the linear displacement δ should be as small as possible. In particular, δ has been constrained not to exceed $\pm 10\ mm$, according to the size of implantable coils of commercial available CIs, employed for inductive powering and data transmission. To this purpose, the fitness function has been defined as:

$$O(P_{av},\delta_M)=\begin{cases}\alpha P_{av} & \delta_M \le o_{\mathrm{M}}\\ \alpha P_{av}-\beta\dfrac{(\delta_M-o_M)}{o_M} & \delta_M > o_{\mathrm{M}}\end{cases} \quad (10)$$

where δ_M is the absolute maximum linear displacementof the oscillating mass; $o_{\mathrm{M}} = 10\ mm$ is the desired maximum of the absolute value of δ; α and β are cost coefficients, respectively valued 1 and 100. In this way, solutions with $\delta_M > o_{\mathrm{M}}$ are penalized.
The details about the GA are reported in Table 1.

In particular, the *Rank scale* and the *Stochastic uniform function* have been selected in order to reduce selection pressure [16].

TABLE I
GA PARAMETERS

Parameter type		Value/Type
Subpopulation		3
Number of individuals per subpopulation		75
Fitness scaling		Rank scale
Selection Function		Stochastic Uniform
Mutation		Gaussian
Cross-over	Type	Scattered
	Fraction	0.8
Migration	Direction	Both
	Fraction	0.2
	Interval	20

TABLE II
OPTIMIZED PARAMETERS

Parameter	Value
m	10^{-2} kg
c	$9.74{\cdot}10^{-7}$ Ns/rad
k	$1.61{\cdot}10^{-7}$ Nm/rad
I	$6.37{\cdot}10^{-8}$ kg m^2
τ	497 m^{-1}

Optimization result corresponding to the 1000th generation.

III. RESULTS AND DISCUSSION

The optimization problem described in this paper aims at maximizing dissipated power while penalizing designs with mass displacements above the threshold o_{M}. The dimensionality of the search space has been reduced from 5 to 4 by using (2). The simulation time over a time window of 160s can be significantly reduced by resorting to discretized functions in the frequency domain. Specifically, the integration method used in this paper is about 120 times faster than Runge-Kutta 4-5. As it can be seen from Figure 2, the two integration methods present no appreciable differences. The use of efficient integration means is of paramount importance when complex input signals are used, such as experimental head acceleration data during human walking.

The most fit individual found by the GA after 1000 generations corresponds to the dynamical parameters reported in Table 2.

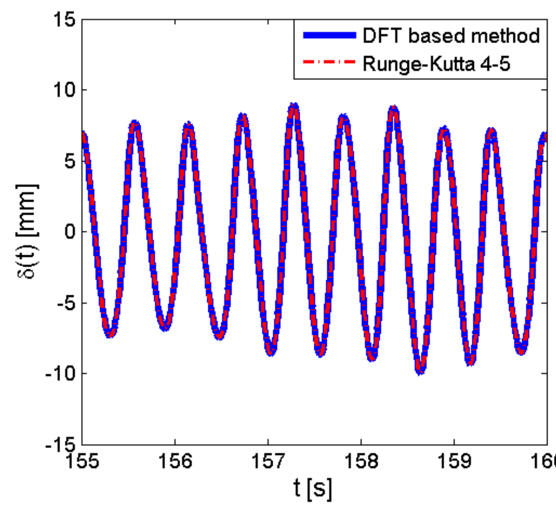

Figure 2.Mass displacement evaluated using DFT method (solid line) and Runge-Kutta 4-5 (dashed line) during the last five seconds of simulation, i.e. from 155 s to 160 s. Even at the end of the simulation period, no difference can be seen.

The total dissipated power corresponding to this individual is 1.343mW. Evidently this value represents the upper bound for the generable electric power because

$$C_e = C - C_m < C.$$

The exact value of the generated electric power depends on the specific electromechanical parameters of the actual transducer.

In order to assess the robustness of the solution found with regards to different input acceleration profiles, the behavior of the EH described in Table 2 has been simulated using additional 4 experimental acceleration profiles. The resulting dissipated mechanical power corresponding to each acceleration profile is reported in Table 3. It can be seen that, compared to the original value, dissipated power increases for two out of four new subjects.

As it concerns the mechanical design, it is worth observing that equation (2) allows one parameter to be freely chosen. This freedom of choice allows the designer to tune the design to meet further constraints that may not be considered during the evolutionary optimization phase (e.g. flywheel diameter, spring stiffness etc.).

IV. CONCLUSIONS AND FUTURE WORK

In this paper a simple and robust optimization method for kinetic EH has been presented. The EH is modeled as a linear second order system excited by head accelerations measured on walking subjects.

The use of discrete transforms allows shrinking down simulation time by two orders of magnitudes compared to numerical methods in the time domain, while preserving a comparable accuracy. Such time reduction allows the use of optimization algorithms, which are simple and robust but computationally demanding, such as GAs.

Future work will be focused on the extension of the proposed method to complete EH model (including the electric subsystem devoted to power management) and develop a prototype in order to validate theoretical assumptions.

TABLE III
OPTIMIZED PARAMETERS

Subject	P_{av} [mW]
1	1.343
2	1.172
3	1.373
4	1.382
5	1.098

Power generated from the DFT based simulation for 5 different subjects using the set of parameters optimized for the first subject.

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