EVOLUTIONARY METHODS FOR DESIGN, OPTIMISATION AND CONTROL
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MIXING OPTIMIZATION WITH EVOLUTION STRATEGIES

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Abstract. Two engineering applications in the field of mixing control are presented, (i) flow in micromixers and (ii) jet flow. Evolution strategies are chosen as optimization method as they are capable of handling multimodal functions, inherent to these applications, in an automated fashion. A covariance matrix adaptation technique is implemented and the results are compared to those from dynamical systems theory and physical understanding.

Key words: evolution strategies, flow control, mixing.

1 INTRODUCTION

The control of mixing has important engineering applications ranging from micromixers for drug delivery to mixing in exhausts of aerodynamic configuration for noise reduction. The optimization of such processes has been subject of several theoretical and experimental works. In the present article, we discuss evolution strategies (ES) as an optimization tool capable of handling diverse requirements for multiscale mixing processes. We present two examples for the optimization of mixing, (i) in micromixers and (ii) in jet flow. Numerical simulations are used to solve the governing equations of the flow. ES's offer several advantages for the optimization of such problems as such processes often involve noise or discontinuities of the objective function, together with a lack of gradient information. Moreover, we expect the function to be multimodal, which is confirmed by the results of our simulations. The inherently parallel character of ES's is exploited in order to compensate for the high computational cost of the simulations.

2 MICROMIXER

Adjusting the active control parameters of a micromixer provides us with the possiblility of highly improved devices for medical applications, such as drug mixing and delivery. In the considered device illustrated in Figure 1, flow in the main channel is manipulated by controlling time-dependent flow from three pairs of secondary channels.

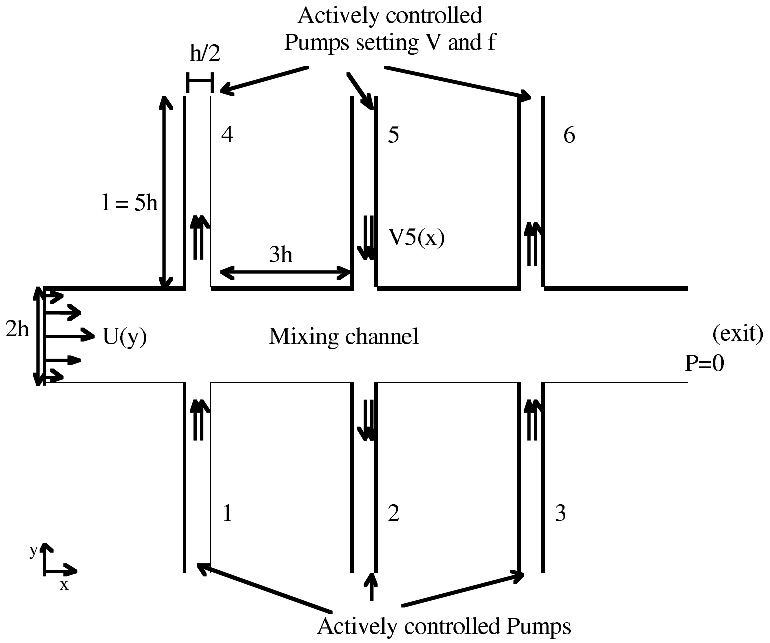

Figure 1: Schematic of the flow configuration

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From these secondary channels, time-dependent cross-flow momentum is imparted on the main channel flow. Actuation parameters are the frequencies of the secondary flow entering through the three pairs of side channels while amplitudes and phase shifts remain constant as recommended in *Volpert et al.* [3] The aim of the optimization is to obtain the parameter vector which leads to the most pronounced mixing in the micromixer. The mixing rate is computed by averaging mixing rates at time instances in the last third of the simulation time, i. e. after the flow has reached steady state. The lengthy calculations associated with the evaluation of the cost function (about 3 CPU hours on a Sun Sparc Ultra-2 processor for one function evaluation) by solving the Navier-Stokes equations are compensated by using parallelized ES's. We implement a derandomized ES with covariance matrix adaptation and with intermediate recombination of all parents, called $(\mu/_{\mathrm{I}}\mu, \lambda)$-CMA-ES.[1] The population consists of $\mu = 2$ parents and $\lambda = 8$ children.

For the actuation of the frequencies in the first and second side channels, the initial and the final parameters and mixing rates are given in Table 1. Note that $m = 0.25$ denotes the case of no mixing and $m = 0$ optimal mixing.

The difficulty with this optimization problem is the unsteadiness in the region where $f_1 \sim f_2$. We found that when the frequencies are similar, the dynamical behavior of the systems changes such that shedding of fluid packages occurs. Therefore, averaging the mixing rate in the last third of the simulation time is not a characteristic measure of the flow behavior. However, we did not learn this behavior before we optimized. A direct search method without a capability of handling noise would not have been able to overcome the above difficulty and would have converged to the unsteady region. The recombination feature of the CMA-ES managed to escape this region. In the beginning of the optimization, a seemingly good function value was found. While continuing the optimization trying to find a better value than the previously found, we checked the dynamical behavior of the flow with the seemingly

Initial frequencies	f_1	0.5
	f_2	0.5
Initial mixing rate	m	0.166
Best frequencies	f_1	0.14
	f_2	0.32
Best mixing rate	m	0.037
Number of function evaluations		420

Table 1: Optimization results

optimal parameters. Hereby, we observed the above mentioned shedding occuring for similar frequencies. To make sure that a real optimum had been found, we had to explore the search space extensively which caused the large number of iterations. If the function had been smooth, we would have stopped the optimization earlier. For the actuation with two frequencies, we reconstructed from the computed points the mixing rate as a function of the actuation parameters, as shown in Fig. 2.

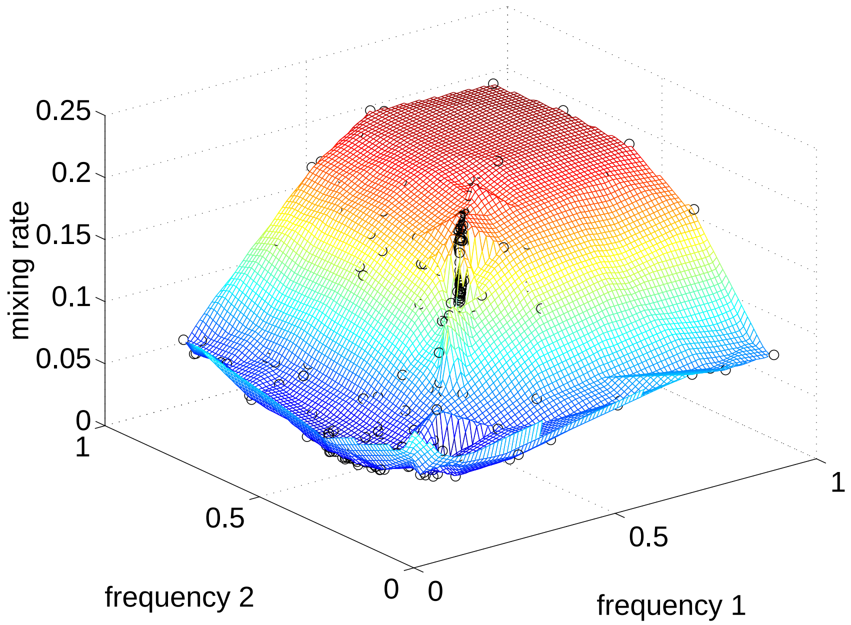

Figure 2: Surface of the mixing rate as a function of the two actuation frequencies, reconstructed from points calculated during the optimization

Due to the high computational cost of the optimization, we could not afford to run another optimization with a different search technique and compare it with the ES. However, for the actuation of the frequencies in three side channel pairs, we were able to compare our optimization results with dynamical system theory. This comparison led to the following conclusion:[2] The algorithm is not only able to identify in an automated fashion effective actuations which have been obtained from theoretical arguments[3] but it can also provide new sets of parameters that further improve mixing.

3 JET FLOW

The control of jet flows has applications in various fields such as combustion, aerodynamic noise, and jet propulsion. The mixing rate of a jet can be altered by applying a suitable excitation at the jet orifice. We examine a prototypical configuration for jet mixing using a vortex filament method to simulate temporally varying jets. The vortex filaments are subject to azimuthal perturbations. Our objective is to maximize the length of all vortex filaments, i.e. to find the perturbation parameters (amplitudes and phase shifts) that cause the greatest perturbation. Optimization parameters are the phase shifts β_j, $(j = 2, ..., 5)$ and the amplitudes ϵ_j, $(j = 1, ..., 5)$ of the azimuthal perturbation. The phase shift β_1 is set to zero. The amplitude $\epsilon_j = 0.2$ given by *Martin and Meiburg*[4] based on linear stability arguments corresponds to a perturbation of 4%. For the optimization, we implement an $(1+1)$-ES running for 300 generations with initial values given by *Martin.*[5] With the phases constrained between 0 and 1, two optimizations are performed. The first optimization, for which the amplitudes are constrained between 0 and 1, yields an increase of 42 % for the filament length. In the second optimization with lower and upper amplitudes of 0 and 0.25, respectively, the filament length is increased by only 1 %. This indicates that the upper limit of the amplitudes has a high impact on the optimization result and thus should be chosen carefully. Figures 3 and 4 show the filament structure of the upper half jet from an axial view. The structure resulting from the first optimization seen in Fig. 3 has longer filaments than the one from the initial state seen in Fig. 2.

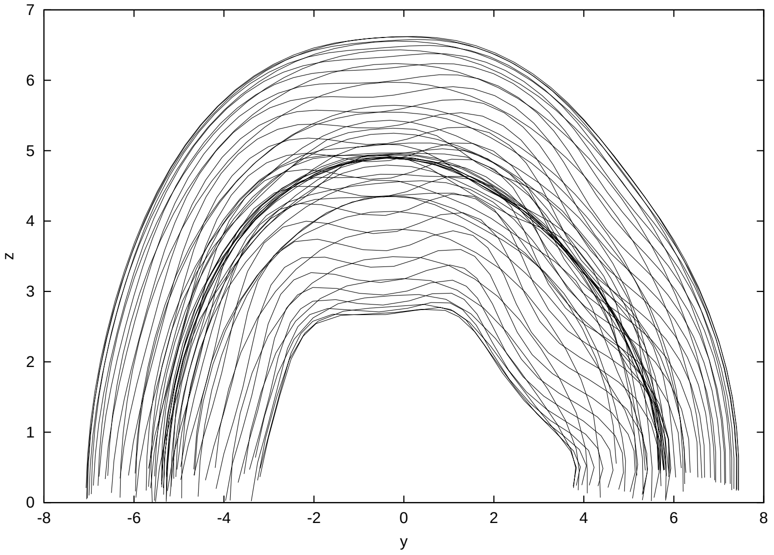

Figure 3: Filament structure of the upper half of the jet, excitation with initial values

4 CONCLUSIONS

We applied evolution strategies on two mixing control problems, (i) flow in micromixers and (ii) jet flow. The results show that these optimization methods are highly suitable for solving such types of applications that are characterized by multimodality and noise. Besides supporting theoretical results, the actuation parameters optimized by evolution strategies yield better mixing than results based on physical intuition.

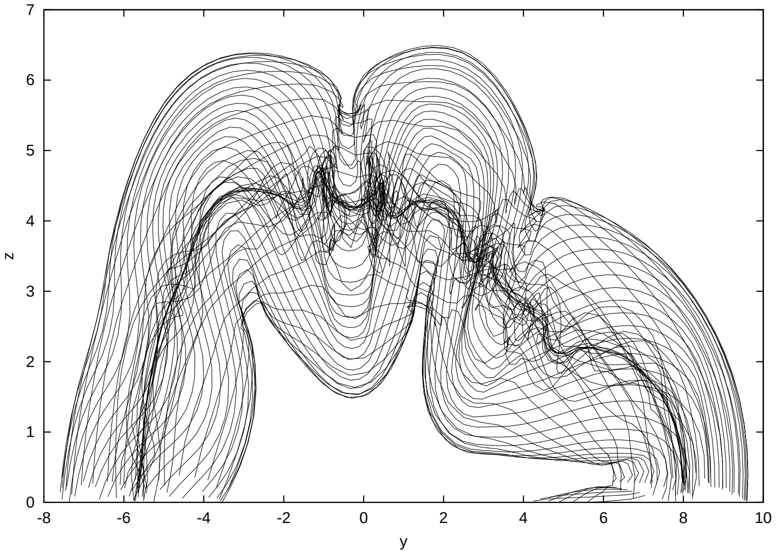

Figure 4: Filament structure of the upper half of the jet, excitation with optimum values (first optimization)

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