Muhammad Asif Zahoor Raja, Muhammad Saeed Aslam, Naveed Ishtiaq Chaudhary, Wasim Ullah Khan, 2018. Bio-inspired heuristics hybrid with interior-point method for active noise control systems without identification of secondary path. *Frontiers of Information Technology & Electronic Engineering*, 19(2):246-259. https://doi.org/10.1631/FITEE.1601028

Bio-inspired heuristics hybrid with interior-point method for active noise control systems without identification of secondary path

Key words: Active noise control (ANC); Filtered extended least mean square (FXLMS); Memetic computing; Genetic algorithms; Interior-point method

Corresponding author: Muhammad Asif Zahoor RAJA
E-mail: Muhammad.asif@ciit-attock.edu.pk
ORCID: http://orcid.org/000-0001-9953-822X

Motivation

Hybrid computing techniques based on bio- and nature-inspired techniques supported by rapid local convergent algorithms have been used extensively for optimization of many linear and nonlinear systems, such as imbalanced data classification, ECG quality assessment, MRI brain image classification, control of a proton exchange membrane fuel cell (PEMFC) stack system, and speaker recognition systems and fractal image compression.

These methods address effectively the problems arising in a variety of fields, including nanotechnology, nonlinear equations, system identification, atomic physics, thermodynamics, plasma physics, robotics systems, and magnetohydrodynamics. These facts are motivation factors for authors for the present study aiming to apply an accurate, effective, and reliable hybrid computing paradigms to nonlinear active noise control systems.

Main idea

Artificial intelligence algorithms based on hybrid computing techniques are designed for ANC systems using variants of genetic algorithms and interior-point method. Variants of GAs are developed by taking different reproduction operators, including crossover, mutation, selection, and elitism to extract the potential for robustness, convergence, multi-objectives, multi-modality, and constrained handling. The optimization power of GA variants is further enhanced by the process of hybridization with an efficient IPM for rapid local convergence. The reliability and effectiveness of the schemes were validated through the results of statistical analysis.

Method

Steps for methodology of hybrid GA-IPMs approaches for ANC are as follows:

Step 1: program and tool initialization for GAs: the initial population with randomly generated bounded real values to represent chromosomes or individuals with elements equal to the number of unknown variables in the ANC model, bounds, and other declarations;

Step 2: fitness evaluation: calculate the fitness value for each individual in the population;

Step 3: ranking: rank each individual on fitness;

Step 4: termination criteria: terminate the execution of the GA if fitness limit or generation executed and go to step 6;

Step 5: reproduction: a new population for each GA variant is created by selection, crossover, and mutations operators. Go to step 2;

Method (Cont'd)

Step 6: hybridization*:* interior point method is used as a hybrid local search algorithm with GA variants;

Initialization: algorithm setting 'interior-point' with bounds, declarations, and initialization of parameters;

Evaluation of fitness;

Termination criteria: terminating the iterative process for adaptation of weights number of cycles are executed or tolerancing limits attains;

Weight updating: for each step increment in IPM optimization, variables are updated;

Step 7: storage*:* store the values of optimized weight vectors along with their fitness, number of generations executed, and time taken by the algorithms for this run;

Step 8: statistical analysis: repeat the procedure from steps 1 – 7 for multiple independent runs for each GA-IPM variant to obtain a sufficiently large set of data for reliable statistical analyses.

Major results

Performance of the proposed algorithm based on 100 independent runs for the ANC system as given in problem 1

Table 5 Performance of our proposed algorithm (GA-IPM) based on 100 independent runs for the ANC system given in problem 1

Method	Fitness (dB)								
	Case 1			Case 2			Case 3		
	Best	Mean	STD	Best	Mean	STD	Best	Mean	STD
GA-IPM-1	43.582	41.223	42.142	43.492	39.950	39.766	43.488	41.747	51.825
GA-IPM-2	43.582	41.196	40.573	43.478	40.747	39.067	43.496	38.929	36.489
GA-IPM-3	43.590	41.573	40.100	43.479	41.068	39.733	43.485	38.255	36.694
GA-IPM-4	43.586	42.644	51.871	43.495	41.619	44.372	43.484	41.821	45.368
GA-IPM-5	43.585	39.718	37.361	43.481	39.440	39.295	43.462	38.895	36.557
GA-IPM-6	43.578	42.098	47.497	43.434	40.567	44.047	43.477	38.497	36.528
GA-IPM-7	43.600	42.011	41.910	43.484	41.403	42.802	43.488	39.719	37.279
GA-IPM-8	43.587	42.602	50.204	43.496	41.936	47.118	43.475	41.950	44.907
GA-IPM-9	43.583	41.170	40.307	43.496	39.851	38.082	43.497	40.781	41.580
GA-IPM-10	43.585	42.613	56.347	43.474	39.900	37.118	43.487	39.499	37.245
GA-IPM-11	43.581	42.655	55.783	43.498	40.867	38.904	43.492	39.611	37.949
GA-IPM-12	43.592	42.793	53.491	43.478	42.838	61.762	43.504	42.519	52.873

Best: maximum fitness; Mean: average fitness; STD: standard deviation

Major results (Cont'd)

Comparison of the proposed algorithms based on the computational complexity parameter for the ANC systems as given in problem 1

Table 6 Comparison of our proposed algorithms based on the computational complexity parameter for the ANC systems given in problem 1

Method	MET (s)			MGs			MFEs		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
GA-IPM-1	31.1	33.7	38.1	334.6	361.7	411.9	23 186	24 308	26 510
GA-IPM-2	27.7	30.9	31.1	325.8	369.4	382.3	22 816	24 646	25 167
GA-IPM-3	28.2	27.3	27.3	333.8	335.6	344.8	23 183	23 256	23 636
GA-IPM-4	25.9	25.2	24.8	316.2	323.9	336.7	22 408	22 733	23 310
GA-IPM-5	29.8	32.8	31.2	338.3	375.3	364.9	23 368	24 973	24 516
GA-IPM-6	27.7	34.9	34.8	319.5	387.2	392.5	22 548	25 455	25 693
GA-IPM-7	24.8	25.3	22.2	302.3	324.7	317.7	21 784	22 737	22 448
GA-IPM-8	23.9	26.5	24.4	397.1	347.8	319.0	21 572	23 762	22 477
GA-IPM-9	26.7	31.6	27.7	311.9	366.3	346.3	22 193	24 554	23 687
GA-IPM-10	28.1	30.6	32.8	328.9	351.6	378.8	22 903	23 846	25 050
GA-IPM-11	26.3	25.9	26.1	308.3	317.0	328.7	22 013	22 404	22 871
GA-IPM-12	28.0	26.1	29.8	321.4	315.5	353.0	22 614	22 353	23 959

MET: mean execution time; MGs: mean number of generations; MFEs: mean value of maximum function evaluations

Conclusions

ANC controllers based on variants of GAs and GA-IPMS were designed by taking different sets of routines for reproduction operators for selection, crossover, and mutation operations, and were applied effectively for the optimization of residual error of ANC systems. The reliability and effectiveness were evaluated for an ANC system with three problems including sinusoidal, random and complex random noises, and for different scenarios of linear or nonlinear primary and secondary paths.

Results showed that all of these schemes achieved relatively small mean values of residual error: for the GAs, around 22.9-27.8 dB for problem 1, 46.6-62.3 dB for problem 2, and 43.5-58.5 dB for problem 3; for the GA-IPMs, the respective values were 36.2-42.8 dB, 46.7-62.4 dB, and 44.2-58.5 dB for the three problems. Comparative studies show that there were no noticeable differences in accuracy, but the results for GA-1 and GA-4 and GA-12 and their respective memetic algorithms were better. Thus, for better performance of bioinspired heuristics based on variants of GA, stochastic uniform, arithmetic and Gaussian routines should be incorporated for selection, crossover and mutation operators, respectively.