

Novel Zigzag-based Benchmark Functions for Bound Constrained Single Objective Optimization

Jakub Kúdela

Institute of Automation and Computer Science, FME, BUT

Jakub.Kudela@vutbr.cz

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- ▶ we propose novel zigzag-based benchmark functions for bound constrained single objective optimization:
 - ▶ non-differentiable
 - ▶ highly multimodal
 - ▶ with “tunable” difficulty

- ▶ we report on computational experiments where we compare two state-of-the-art algorithms and one standard EA on a set of problems that utilize the new benchmark functions

Novel Benchmark Functions

The new benchmark functions are constructed as follows. First, we devise a “zigzag” function $z(x)$. For given parameters $k > 0, m > 0$ the zigzag function $z(x)$ at a point $x \in \mathbb{R}$ is computed as:

$$z(x) = \begin{cases} m\left(\frac{1}{2} + (-1)^{\lceil kx \rceil} \left(\frac{\lceil kx \rceil + \lfloor kx \rfloor}{2} - kx\right)\right), & \text{if } (kx) \notin \mathcal{Z} \\ 0, & \text{if } \frac{kx}{2} \in \mathcal{Z} \\ m, & \text{otherwise,} \end{cases}$$

where $\frac{2}{k}$ is the period and m is the amplitude of the zigzag function, as depicted in following figure.

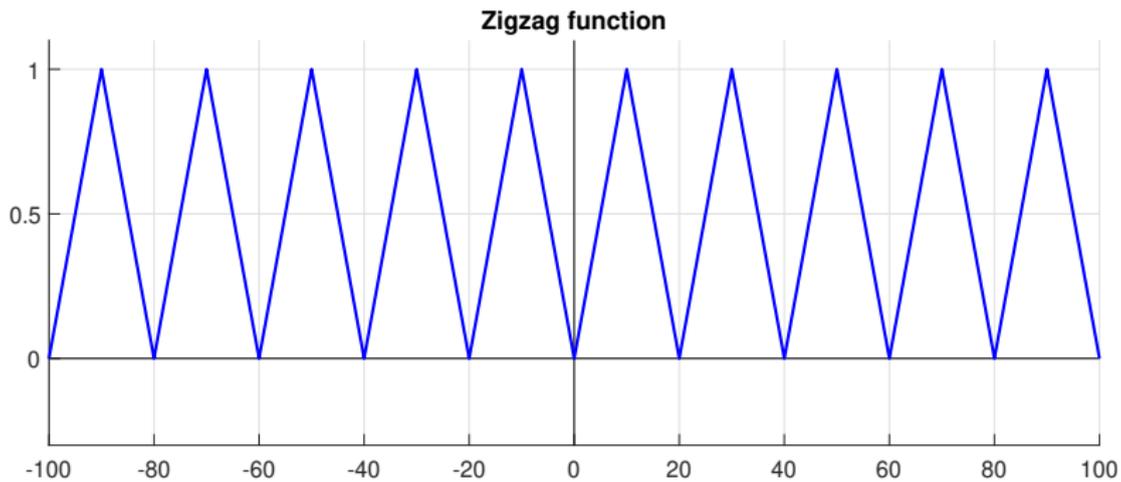


Figure: Zigzag function $z(x)$ with $k = 0.1$, $m = 1$.

The next step is a construction of a multimodal function $f(x)$:

- ▶ a sum of an absolute value of a high degree polynomial with one root in zero and an absolute value function
- ▶ the scaling of these two parts is such that the function values on the interval $[-200, 200]$ lie between $[0, 200]$ (allows composing the function with itself without severe numerical difficulties)
- ▶ the “polynomial” part of the function f is then multiplied with the zigzag function $z(x)$
- ▶ the particular choice for the function $f(x)$ in this paper is the following:

$$f(x) = 3 \cdot 10^{-9} |(x-50)(x-190)x(x+70)(x+180)| z(x) + 0.2|x|$$

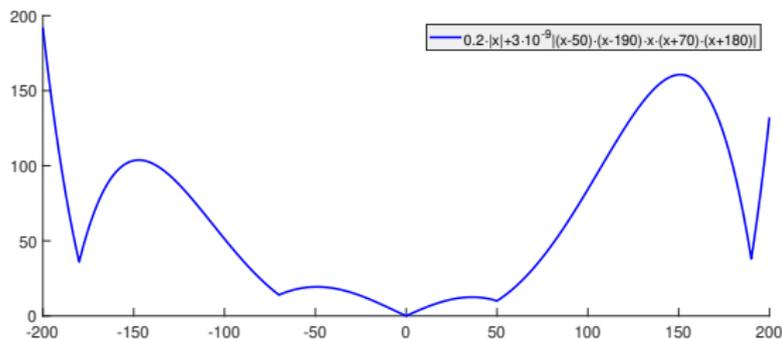
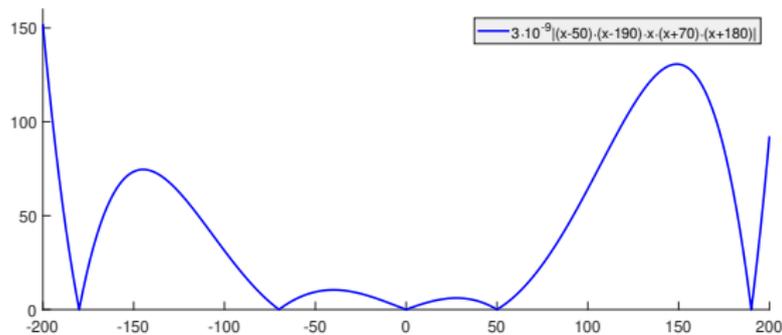
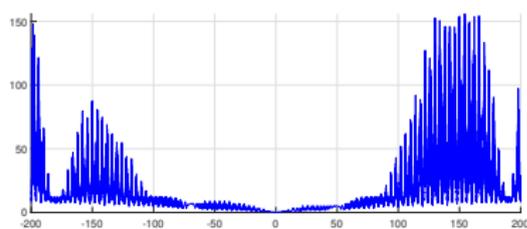
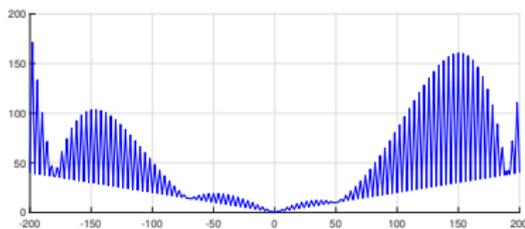
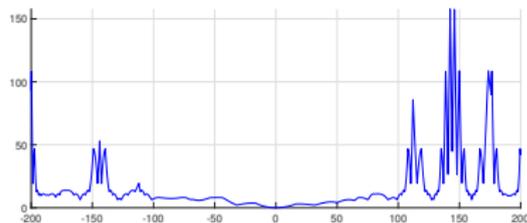
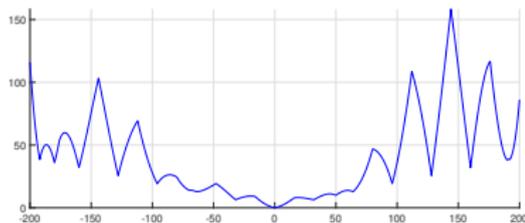


Figure: Partial construction of the function $f(x)$.



$f(x)$ and $f(f(x))$ for $k = 2^{-1}$



$f(x)$ and $f(f(x))$ for $k = 2^{-4}$

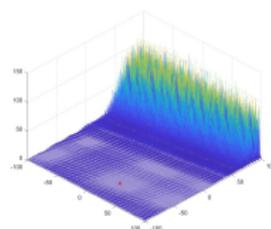
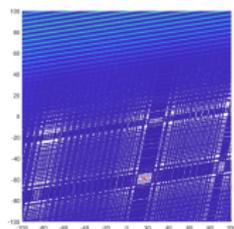
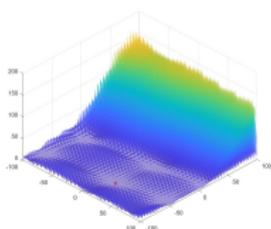
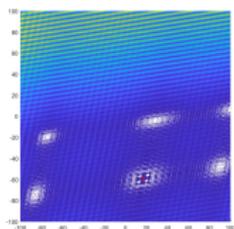
Figure: Functions $f(x)$ (left) and $f(f(x))$ (right) for different values of parameter k

- ▶ the function f has a single global optimum point in 0, is non-differentiable and highly multimodal (the “degree of multimodality” depending on the parameter k)
- ▶ finally, the two proposed benchmark functions $F_1(\mathbf{x})$ and $F_2(\mathbf{x})$, for $\mathbf{x} = [x_1, \dots, x_D]^T$ and $\mathbf{x} \in [-100, 100]^D$, are the following:

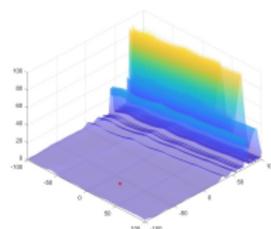
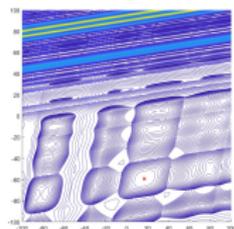
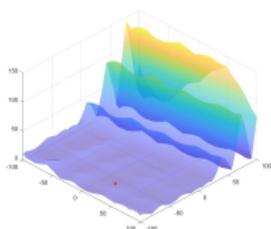
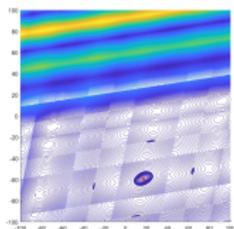
$$f_1(\mathbf{x}) = \sum_{i=1}^D f(x_i), \quad F_1(\mathbf{x}) = f_1(\mathbf{M}_1(\mathbf{x} - \mathbf{s}_1)),$$
$$f_2(\mathbf{x}) = \sum_{i=1}^D f(f(x_i)), \quad F_2(\mathbf{x}) = f_2(\mathbf{M}_2(\mathbf{x} - \mathbf{s}_2)),$$

where $\mathbf{s}_1, \mathbf{s}_2 \in [-100, 100]^D$ are random shifts of the optimal solution and $\mathbf{M}_1, \mathbf{M}_2$ are random rotation/scaling matrices, with eigenvalues in the range $[0.5, 1]$

values can be found in: <https://github.com/JakubKudela89/Zigzag>



$F_1(\mathbf{x})$ and $F_2(\mathbf{x})$ for $k = 2^{-1}$



$F_1(\mathbf{x})$ and $F_2(\mathbf{x})$ for $k = 2^{-4}$

Figure: Contour and surface plots of the benchmark functions $F_1(\mathbf{x})$ (left) and $F_2(\mathbf{x})$ (right) for different values of parameter k . The optimum is highlighted by a red marker.

Computational Experiments and Results

For computational experiments with the two benchmark functions we chose three algorithms:

- ▶ the first algorithm is the canonical particle swarm optimization (PSO) algorithm
- ▶ the second algorithm is the winner of the CEC'20 Competition on Single Objective Bound Constrained Optimization, the Improved Multi-operator Differential Evolution (IMODE) algorithm
- ▶ the third algorithm is the runner-up of the same competition, the Adaptive Gaining-Sharing Knowledge (AGSK) based algorithm

We use the same benchmark rules as the CEC'20 competition:

- ▶ the three algorithms are evaluated on the two benchmark functions with $D = [5, 10, 15, 20]$ dimensions
- ▶ parameter $k = [2^0, 2^{-1}, 2^{-2}, 2^{-3}, 2^{-4}]$
- ▶ search space of $[-100, 100]^D$
- ▶ maximum number of function evaluations were set to 50,000, 1,000,000, 3,000,000 and 10,000,000 fitness function evaluations for problems with $D = [5, 10, 15, 20]$
- ▶ all algorithms were run 30 times to obtain representative results
- ▶ for both IMODE and AGSK, we use the same parameter settings that they used in the CEC'20 competition

Results for $F_1(x)$:

		D = 5			D = 10			D = 15			D = 20		
		PSO	AGSK	IMODE	PSO	AGSK	IMODE	PSO	AGSK	IMODE	PSO	AGSK	IMODE
$k = 2^0$	min	0	0	9.37e-06	1.73e-04	0	1.12e+00	2.80e-01	2.53e+00	2.70e+00	1.01e+00	5.23e+00	6.06e+00
	median	0	0	1.76e-02	1.64e-01	5.22e-01	1.91e+00	1.91e+00	5.06e+00	3.90e+00	2.87e+00	7.67e+00	8.44e+00
	mean	0	1.87e-02	6.98e-02	4.08e-01	7.61e-01	1.93e+00	1.92e+00	4.89e+00	3.86e+00	3.18e+00	7.67e+00	8.51e+00
	max	0	2.77e-01	4.08e-01	2.42e+00	2.37e+00	2.73e+00	4.33e+00	6.31e+00	5.24e+00	6.94e+00	9.72e+00	1.03e+01
	std	0	5.47e-02	7.46e-01	6.57e-01	7.48e-01	4.71e-01	1.12e+00	9.45e-01	5.92e-01	1.60e+00	1.15e+00	9.07e-01
$k = 2^{-1}$	min	0	0	6.75e-08	9.22e-06	0	3.68e-01	8.81e-01	0	2.64e+00	1.12e+00	5.52e+00	7.27e+00
	median	0	0	8.84e-04	4.45e-01	9.04e-01	2.34e+00	3.38e+00	4.90e+00	4.02e+00	3.39e+00	8.76e+00	8.85e+00
	mean	0	6.89e-02	4.23e-02	6.80e-01	1.02e+00	2.25e+00	3.49e+00	4.80e+00	3.99e+00	3.60e+00	8.67e+00	8.88e+00
	max	2.57e-08	1.00e+00	2.67e-01	1.91e+00	2.74e+00	3.19e+00	6.58e+00	6.11e+00	5.10e+00	7.61e+00	1.03e+01	1.05e+01
	std	0	2.00e-01	7.98e-02	6.34e-01	7.84e-01	6.64e-01	1.64e+00	1.14e+00	5.72e-01	1.38e+00	1.13e+00	7.54e-01
$k = 2^{-2}$	min	0	0	0	2.14e-03	0	1.31e+00	9.60e-01	3.01e+00	5.40e-01	8.02e-01	6.65e+00	4.25e+00
	median	0	1.10e-07	1.34e-04	6.44e-01	1.67e+00	2.13e+00	3.47e+00	5.01e+00	3.16e+00	3.37e+00	8.49e+00	8.08e+00
	mean	3.73e-02	3.25e-02	2.99e-02	6.24e-01	1.59e+00	2.12e+00	3.70e+00	4.82e+00	3.04e+00	3.53e+00	8.48e+00	7.91e+00
	max	8.02e-01	2.87e-01	5.22e-01	1.61e+00	2.99e+00	3.65e+00	7.54e+00	5.72e+00	4.06e+00	7.86e+00	1.01e+01	9.61e+00
	std	1.55e-01	7.68e-02	1.13e-01	3.26e-01	7.84e-01	5.39e-01	1.86e+00	7.13e-01	7.79e-01	1.30e+00	9.56e-01	1.09e+00
$k = 2^{-3}$	min	0	0	0	1.48e-05	0	8.41e-04	0	2.94e+00	8.67e-04	0	5.96e+00	2.74e+00
	median	0	0	0	3.79e-02	3.20e-01	1.55e+00	3.85e+00	4.65e+00	9.60e-01	3.70e+00	7.91e+00	5.83e+00
	mean	0	2.79e-04	1.52e-06	4.21e-01	8.00e-01	1.41e+00	3.75e+00	4.58e+00	8.23e-01	3.64e+00	8.09e+00	5.78e+00
	max	0	8.14e-03	2.22e-05	1.92e+00	2.74e+00	2.36e+00	8.06e+00	5.71e+00	1.65e+00	7.17e+00	1.05e+01	7.53e+00
	std	0	1.48e-03	5.48e-06	5.51e-01	9.79e-01	6.59e-01	1.92e+00	6.86e-01	5.20e-01	1.71e+00	1.04e+00	1.28e+00
$k = 2^{-4}$	min	0	0	0	3.97e-06	0	0	0	0	0	0	8.83e+00	1.28e+00
	median	0	0	0	4.59e-03	0	0	3.20e+00	3.83e+00	0	3.07e+00	7.60e+00	3.23e+00
	mean	0	0	0	2.00e-01	8.53e-02	3.49e-07	3.41e+00	3.62e+00	0	3.21e+00	7.37e+00	2.96e+00
	max	0	0	0	1.28e+00	1.28e+00	7.75e-06	8.88e+00	4.99e+00	0	6.12e+00	9.06e+00	3.97e+00
	std	0	0	0	4.11e-01	3.24e-01	1.48e-06	2.11e+00	1.19e+00	0	1.60e+00	1.17e+00	7.34e-01

Results for $F_2(x)$:

		D = 5			D = 10			D = 15			D = 20		
		PSO	AGSK	IMODE	PSO	AGSK	IMODE	PSO	AGSK	IMODE	PSO	AGSK	IMODE
$k = 2^0$	min	0	0	4.44e-05	1.70e-05	0	1.01e-01	9.66e-02	3.64e-01	2.40e-01	8.69e-02	6.03e-01	5.26e-01
	median	0	6.20e-03	1.20e-02	1.68e-02	1.69e-01	2.13e-01	3.65e-01	6.85e-01	4.15e-01	4.75e-01	9.09e-01	8.01e-01
	mean	1.75e-02	2.24e-02	1.84e-02	4.03e-02	1.61e-01	2.03e-01	4.91e-01	6.47e-01	4.00e-01	4.99e-01	8.89e-01	7.81e-01
	max	1.30e-01	1.25e-01	5.18e-02	1.92e-01	2.87e-01	2.61e-01	1.56e+00	8.40e-01	4.94e-01	2.23e+00	1.08e+00	9.30e-01
	std	2.95e-02	3.19e-02	1.72e-02	4.95e-02	7.54e-02	4.38e-02	4.34e-01	1.12e-01	6.23e-02	3.87e-01	1.24e-01	9.74e-02
$k = 2^{-1}$	min	0	0	7.68e-06	3.68e-07	0	1.31e-01	1.11e-02	3.73e-01	2.90e-01	5.30e-02	4.25e-01	6.77e-01
	median	0	9.77e-08	1.91e-03	7.61e-03	1.22e-01	2.39e-01	3.16e-01	6.73e-01	5.40e-01	3.42e-01	9.89e-01	1.18e+00
	mean	0	3.74e-03	5.26e-03	2.32e-02	1.29e-01	2.52e-01	3.41e-01	6.44e-01	5.32e-01	3.81e-01	9.98e-01	1.16e+00
	max	0	3.67e-02	2.81e-02	1.23e-01	3.67e-01	4.12e-01	8.91e-01	8.59e-01	6.68e-01	9.25e-01	1.32e+00	1.37e+00
	std	0	9.20e-03	6.91e-03	3.68e-02	1.08e-01	7.34e-02	2.24e-01	1.21e-01	9.66e-02	2.33e-01	2.14e-01	1.39e-01
$k = 2^{-2}$	min	0	0	1.32e-08	8.14e-06	0	4.56e-02	1.06e-01	1.38e-01	1.57e-01	2.05e-01	2.69e-01	5.38e-01
	median	0	0	1.17e-05	6.24e-03	1.29e-01	2.12e-01	3.68e-01	4.74e-01	3.11e-01	4.06e-01	9.12e-01	8.98e-01
	mean	1.83e-04	2.44e-03	1.99e-03	2.82e-02	1.27e-01	1.96e-01	4.00e-01	4.57e-01	3.20e-01	4.27e-01	8.84e-01	8.82e-01
	max	5.49e-03	2.35e-02	2.71e-02	2.00e-01	3.62e-01	3.38e-01	9.49e-01	6.54e-01	4.37e-01	7.04e-01	1.25e+00	1.10e+00
	std	1.00e-03	5.73e-03	5.61e-03	4.80e-02	8.63e-02	7.96e-02	2.18e-01	1.23e-01	6.62e-02	1.44e-01	1.91e-01	1.33e-01
$k = 2^{-3}$	min	0	0	0	6.19e-08	0	4.74e-02	0	1.12e-01	1.45e-02	7.57e-02	2.93e-01	2.98e-01
	median	0	0	3.32e-08	1.38e-04	7.16e-02	8.30e-02	3.02e-01	2.60e-01	1.04e-01	2.53e-01	5.87e-01	3.93e-01
	mean	1.08e-03	1.04e-03	4.02e-06	2.84e-02	7.51e-02	9.08e-02	2.76e-01	2.54e-01	9.97e-02	2.77e-01	5.52e-01	3.96e-01
	max	3.26e-02	1.42e-02	4.90e-05	1.27e-01	1.59e-01	1.72e-01	5.15e-01	3.32e-01	1.63e-01	4.94e-01	7.02e-01	5.05e-01
	std	5.95e-03	3.35e-03	1.07e-05	4.18e-02	5.08e-02	3.00e-02	1.30e-01	5.24e-02	3.69e-02	1.21e-01	9.42e-02	4.94e-02
$k = 2^{-4}$	min	0	0	0	6.19e-08	0	0	0	0	0	2.19e-02	1.12e-01	9.46e-05
	median	0	0	0	4.38e-05	0	0	8.40e-02	1.53e-01	0	1.97e-01	3.05e-01	1.54e-01
	mean	0	0	0	2.97e-03	0	1.00e-06	1.22e-01	1.47e-01	0	2.01e-01	2.91e-01	1.52e-01
	max	0	0	0	2.19e-02	0	1.12e-05	3.91e-01	2.28e-01	0	3.70e-01	3.85e-01	2.16e-01
	std	0	0	0	7.57e-03	0	2.68e-06	1.16e-01	4.86e-02	0	7.70e-02	6.51e-02	4.33e-02

- ▶ it is clear from the results that both the benchmark functions are not “impossible” to optimize, as there were plenty of instances where the algorithms found the optimal solution
- ▶ however, the instances are not “too easy” so that the algorithms find the optimum reliably – this, in our opinion, makes these benchmark functions worth investigating
- ▶ another observation to be made is that for both test functions, reducing the zigzag parameter k really reduces the complexity of the problems. In particular, the changes from $k = 2^{-2}$ to $k = 2^{-3}$ and then to $k = 2^{-4}$ seem to have the biggest impact, while the statistical results for problems with $k = [2^0, 2^{-1}, 2^{-2}]$ are relatively stable
- ▶ unsurprisingly, the difficulty of the test problems also increases with the dimension D

- ▶ the most surprising results come from the comparison of the three algorithms
- ▶ overall, on both of the newly proposed benchmark functions, neither of the two best algorithms from the CEC'20 competition performed significantly better than a standard PSO
- ▶ we argue that this a prime reason for investigating these benchmark functions even further and for including them in future competitions and benchmark suits
- ▶ future research will encompass comparing a wider selection of algorithms, and developing multimodal benchmark functions using the presented technique

Thank you for your attention!