

Design of a Surrogate Model Assisted $(\mu/\mu, \lambda)$ -ES

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Surrogate models have been widely used to assist evolutionary algorithms (EAs) to avoid unnecessary objective function evaluations. The cost is reduced by substituting the true objective function evaluation with a cheap but inaccurate estimate using the surrogate model. The surrogate model is built on the knowledge gained in previous iterations. Using surrogate assisted $(1+1)$ -ES for simple model and single steps have been studied, but the effect of actual inferior parent resulted from an inaccurate surrogate estimation and the corresponding poor step size are not well understood. We study the behaviour using a surrogate model assisted $(\mu/\mu, \lambda)$ -ES using a population instead of a single offspring with the hope to possibly address the issue. The behaviours of the two strategies are compared using several test functions.

Additional Key Words and Phrases: $(\mu/\mu, \lambda)$ -ES, Surrogate Model, Evolutionary algorithms(EAs), Gaussian Process

ACM Reference format:

Jingyun Yang and Dirk V. Arnold. 2018. Design of a Surrogate Model Assisted $(\mu/\mu, \lambda)$ -ES. 1, 1, Article 1 (November 2018), 13 pages. <https://doi.org/>

1 INTRODUCTION

Evolution strategies (ESs) have been widely utilized to solve optimization problems where the true objective function evaluation is computationally-intensive. Various attempts have been made to reduce the cost by extracting the information obtained from points evaluated in previous iterations. Such information yields insights into better mutation and recombination that help generate and select promising offspring. One way is to use the cumulative step size adaptation (CSA) [19] that builds an evolution path based on the history step size (mutation) of ESs, the population in the next iteration is generated based on the mutation adapted by the evolution path.

The history information could be used to construct a surrogate model, referred either as a local approximation or a global approximation to the true objective function [16]. There are a range of surrogate models and a survey of the development can be found by Jin [14] and Loshchilov [18]. Those algorithms are usually heuristic by nature and the behaviour of each step is likely not well interpreted. Recent work in surrogate assisted EAs tend to use sophisticated algorithm where surrogates are combined or the model is updated online according to some heuristic. Comparison is often made by comparing the performance using the algorithm with and without model assistance where the behaviour of the surrogate is not well simulated. In this context, an approach that could simulate the surrogate would be helpful in understanding the surrogate behaviour, leading to potential modification for surrogate update or parameter-setting. A surrogate that models the objective function with desired precise gains benefit especially for algorithms that requires

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Manuscript submitted to ACM

a large population size for good performance. The computational saving largely lies in the saved evaluations outshine the potential poor step resulted from relative inaccurate estimation of candidate solutions.

This paper intend to improve the understanding of the impact of population size on surrogate-assisted ESs' by analyzing using simple test functions with strong theoretical basis and established baselines. The paper is organized as follows: In Section 2 we give a brief review of related background, in Section 3 we propose a local surrogate model-assisted $(\mu/\mu, \lambda)$ -ES and study its behaviour on sphere functions. Based on the existing knowledge and step behaviour, in Section 4, we then propose a combined step size adaptation mechanism for the this algorithm, analyze the performance using several test functions and compare the result with a surrogate model-assisted $(1+1)$ -ES [17]. The experimental result is followed by a discussion and future work in Section 5.

2 RELATED WORK

2.1 Surrogate Model

Using an approximate model to reduce computational cost can be traced back to 1960s [7]. Some successful surrogated models include but are not limited to Polynomial Regression (PR, response surface methodology) [11], Gaussian Process (GP, Kriging models) [13], Artificial neural networks [23]. There are two types of surrogate models, global surrogate model and local surrogate model. ES using global surrogate model based on Kring was examined by Ratle [20]. Another ES using global surrogate model based on Artificial neural networks was constructed by Jin [15] which gives an imperial criterion on using the true objective function or the surrogate model to evaluate the offspring. Ulmer et al [24] and Buche et al [5] also applied GP as surrogate models in ES. But the performance of global surrogate models degrade as the dimension of the data increases, known as *curse of dimensionality*. Since the performance of ES is straightly affected by the surrogate model accuracy, online surrogates has been introduced by using a surrogate-adaptation mechanism that updated the model according to some heuristic. Loshchilov et al [12] uses . Online local surrogate models [25] can be constructed using methods like radial basis function (RBF) [8] to replace the global surrogate model, where the surrogate model is updated online, giving a more accurate estimation compared with the global surrogate model.

There are various surrogate-assisted EAs integrating global and local surrogate models or using a combination of heuristics. These methods tend to be sophisticated for good performance, while few literatures have *systematically investigated???* the surrogated-assisted $(\mu/\mu, \lambda)$ -ES. One exception is what Chen and Zou [6] proposed but yet incomplete in terms of two aspects. Firstly, it uses a linear surrogate that cannot give a precise estimate when coordinate transform is applied, the precondition to solve a generalized optimization problem [17]. Secondly, it does not include a step size adaptation mechanism. Besides that, Ulmer et al [9] proposed a Model Assisted Steady-State Evolution Strategy (MASS-ES), which is a $(\mu + \lambda)$ -ES that is a $(1+1)$ -ES when we set $\mu = \lambda = 1$. But the behavior of step size adaptation is unclear given the proposed conditions.

wonder should focus more on surrogateassisted(1 + 1) – ES, surrogateassistedmmml – ES, possibly most CMA – ES

There is a wealth of literatures for solving black box optimization using $(1+1)$ -ES on unimodal test problems given the convergence property of convex functions. Kayhani and Arnold [17] proposed a surrogated-assisted $(1+1)$ -ES that investigates the acceleration and single step behaviour of the algorithm using GP based local surrogate. In this algorithm, the local surrogate acts as a filter and is updated every time when a true objective function is made. Since $(1+1)$ -ES generate a single offspring per iteration and is not as robust as $(\mu/\mu, \lambda)$ especially in the presence of surrogate (bias due to choice of points), we argue that it is natural to ask to what degree the choice of population can benefit the ES in terms of robustness and acceleration.

2.2 Step size adaptation

The step size of $(\mu/\mu, \lambda)$ -ES is commonly adapted using cumulative step size adaptation (CSA) proposed by Ostermeier et al [19]. In each iteration, $(\mu/\mu, \lambda)$ -ES generate λ candidate solutions $y_i \in \mathbb{R}^N, i = 1, \dots, \lambda$ from a parental population $x_i \in \mathbb{R}^N, i = 1, \dots, \mu$ and the centroid of the parent population is $x = 1/\mu \sum_{i=1}^{\mu} x_i$ where $\mu < \lambda$. The parental population is replaced by the best μ candidate solutions generated by $y_i = x + \sigma z$ where $\sigma \in \mathbb{R}$ is a scalar referred to as the step size and $z \in \mathbb{R}^N$ as the mutation. For a strategy with ideally adapted step size, each step should be uncorrelated. If the connectives are negatively correlated, the step size should be decreased. In contrast, if the connective steps are positively correlated, the steps are pointing to the same direction. Then a number of small steps can be replaced by fewer large steps and therefore, the step size should increase.

To decide the correlation, information from previous steps and mutations are cumulated. By comparing the step size with its expected length under random selection, the step size is adapted according to its expected length. It increases if the length is less than expected and decrease otherwise.

Define the search path as

$$p_{k+1} \leftarrow (1 - c)p_k + \sqrt{\mu c(2 - c)}z, \quad (1)$$

where $0 < c \leq 1$ is the proportion of history information retained and passed to the evolution path in the next iteration, $\sqrt{\mu c(2 - c)}$ is a normalization constant that updates the evolution path from the mutation of this iteration and z the mutation obtained by averaging the best μ candidate solutions generated.

The step size is adapted

$$\sigma \leftarrow \sigma \exp \left(\frac{c}{d} \left(\frac{\|p\|}{E\|N(0, I)\|} \right) \right), \quad (2)$$

where $E\|N(0, I)\|$ is the expected length of the search path p and can be approximated as $E\|N(0, I)\| \approx \sqrt{n}(1 - 1/4n + 1/21n^2)$. In Section 4, the detail will be discussed.

wonder if something is missing feels not sufficient

3 ANALYSIS

To understand the potential implications of using surrogate models in EAs with varying population size, in this section, we use a simple model that applies a surrogate on the population. Specifically, we propose an EA that, in each iteration, a population of new λ candidate solutions are generated and then evaluated by the surrogate instead of true objective function calls and a selection based on the inaccurate surrogate estimate is done followed by a true objective function evaluation for the centroid of the selected referred to as the parent for next iteration. We assume that the inaccurate estimate of the surrogate model is a Gaussian random variable with mean equals the true objective function value of the candidate solution with some variance that describes the accuracy of the surrogate model. So, we can apply the technique of analyzing ESs's behaviours in the presence of Gaussian noise [3]. The analysis could be extended to biased surrogate models where the distribution mean is different from the exact objective function value[17]....

Comparison based surrogate model

Consider the minimization of the quadratic sphere $f : \mathbb{R}^N \rightarrow \mathbb{R}$ with $f(x) = x^T x$ where the surrogate model assisted $(\mu/\mu, \lambda)$ -ES is applied. This section will use the surrogate model described above to replace the true objective function calls of candidate solutions in each iteration, inaccurate but at vanishing cost. We first consider a simple iteration of the

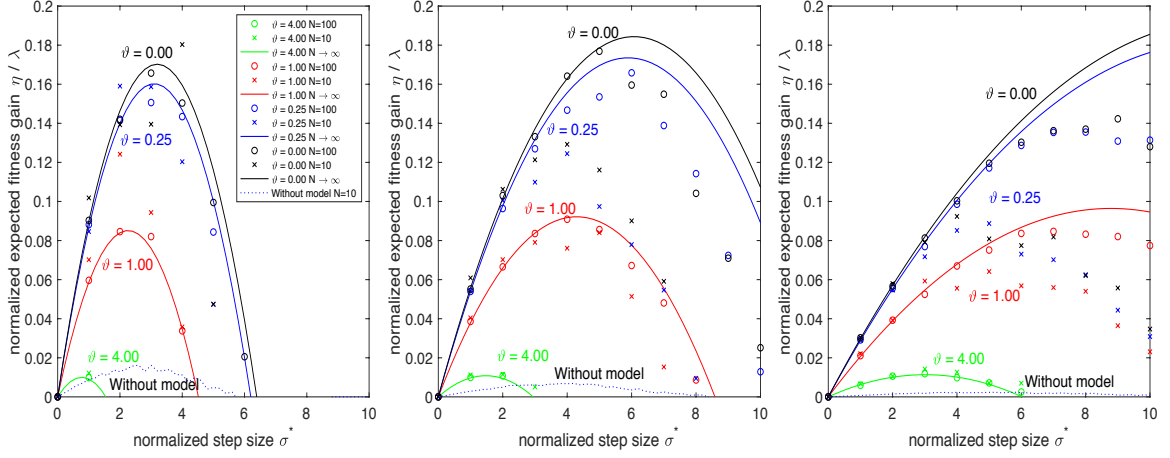


Fig. 1. The figures from left to right shows the expected single step behaviour of the surrogate model assisted $(\mu/\mu, \lambda)$ -ES with unbiased Gaussian distributed surrogate error with $\lambda = 10, 20, 40$ respectively where $\mu = \lceil \lambda/4 \rceil$. The solid lines are the results obtained analytically when $n \rightarrow \infty$, while the dotted line below illustrates the corresponding performance ($n = 10$) of the $(\mu/\mu, \lambda)$ -ES without model assistance. The dots represents the experimental result for $n = 10$ (crosses) and $n = 100$ (circles).

strategy. In each iteration, a population size of λ new candidate solutions $y_i \in \mathbb{R}^N, i = 1, \dots, \lambda$ are generated from μ parents $x_i \in \mathbb{R}^N, i = 1, \dots, \mu$, where $\lambda > \mu$. The parental population with size μ are replaced by the best μ candidate solutions $y_{i:\lambda}, i = 1, 2, \dots, \mu$ evaluated by the surrogate model with fitness estimate $f_\epsilon(y_{i:\lambda}) \leq f_\epsilon(y_{j:\lambda}), 1 \leq i < j \leq \lambda$ at vanishing cost. For each of the λ candidate solutions $y_i = x + \sigma z$ where the parent $x = \sum_{i=1}^n x_i / \mu$, the centroid of the parental population is obtained through intermediate recombination, $z \in \mathbb{R}^N$ is a standard normally distributed random vector, $\sigma > 0$ is the step size of the strategy that the adaptation is discussed in Section 4. The strategy uses the surrogate model to obtain a fitness estimate of the candidate solution $f_\epsilon(y_i), 1 \leq i \leq \lambda$ and by the assumption the estimate has mean $f(y_i)$ with some standard deviation $\sigma_\epsilon > 0$ (surrogate model error also as fitness noise [2]). Better surrogate model results in smaller model error σ_ϵ . For the λ new candidate solutions $f_\epsilon(y_i) < f_\epsilon(y_j), 1 \leq i < j \leq \lambda$ indicates the estimated objective function value of y_i is superior to y_j and therefore the best μ candidate solutions are selected, replacing the old parental population of size μ (used for offspring generation in next iteration), while the other inferior candidate solutions are discarded. Therefore, in each iteration only one objective function call is made in evaluating the fitness of the parent (centroid of parental population). The surrogate essentially does a pre-selection for $(\mu/\mu, \lambda)$ -ES over candidate solutions, avoiding the unnecessary objective function calls determined by the surrogate model.

Decomposition of z , first proposed by Rechenberg [21] can be used to study the expected step size of the strategy. We can decompose the vector z as a vector sum $z = z_1 + z_2$, where z_1 is in the direction of the negative gradient of the objective function $\nabla f(x)$, while z_2 orthogonal to z_1 . We have z_1 standard normally distributed, while $\|z_2\|^2$ χ -distributed with $N - 1$ degree of freedom and $\|z_2\|^2 / N \xrightarrow{N \rightarrow \infty} 0$ (see reference theorem [Dirk's slides]). Denote $\delta = N(f(x) - f(y)) / (2R^2)$ where $R = \|x\|$ is the distance to the optimal, we further introduce normalized step size $\sigma^* = N\sigma / R$ and $z_{\text{step}} = \sum_{i=1}^\mu z_{i:\lambda}$ (the averaged z taken by the best μ candidate solutions). The normalized fitness

advantage of y over x follows

$$\begin{aligned}\delta &= \frac{N}{2R^2} (x^T x - (x + \sigma z_{\text{step}})^T (x + \sigma z_{\text{step}})) \\ &= \frac{N}{2R^2} (-2\sigma x^T z_{\text{step}} - \sigma^2 \|z_{\text{step}}\|^2) \\ &\stackrel{N \rightarrow \infty}{=} \sigma^* z_{\text{step},1} - \frac{\sigma^{*2}}{2},\end{aligned}\tag{3}$$

where $z_{\text{step},1}$, the component of z_{step} pointing to the negative gradient of $f(x)$, is normally distributed and $\stackrel{N \rightarrow \infty}{=}$ denotes the convergence of the distribution $\|z_{\text{step}}\|^N / N = 1$. We further introduce $\sigma_\epsilon^* = N\sigma_\epsilon / (2R^2)$, the normalized surrogate model error (also referred to as the normalized fitness noise in Noise Sphere from Arnold and Beyer [2]). The estimate of true objective function value of y_i is $f_\epsilon(y_i) = f(y_i) + \sigma_\epsilon z_\epsilon$, $z_\epsilon \in \mathbb{R}$ is standard normally distributed.

The actual normalized fitness advantage of y using the surrogate model is

$$\delta_\epsilon = \delta + \sigma_\epsilon^* z_\epsilon\tag{4}$$

The expected value of the normalized change in objective function value

$$\begin{aligned}\Delta &= -\frac{N}{2} E [\log f(y) - \log f(x)] \\ &= -\frac{N}{2} E \left[\log \frac{f(x^{t+1})}{f(x^t)} \right],\end{aligned}\tag{5}$$

where y^t is the centroid of parental population in timestamp t , the equation is normalized in terms of dimensionality.

Since the fitness of λ offspring generated are evaluated by the surrogate model with vanishing cost. The objective function evaluation per iteration is 1 instead of λ (for $(\mu/\mu, \lambda)$ -ES), therefore the normalized progress rate when dimensionality $N \rightarrow \infty$, by substituting λ with 1 in equation (7) from [4] is

$$\eta = \frac{1}{1} E[\Delta] = \frac{\sigma^* c_{\mu/\mu, \lambda}}{\sqrt{1 + \vartheta^2}} - \frac{(\sigma^*)^2}{2\mu},\tag{6}$$

where $\vartheta = \sigma_\epsilon^* / \sigma^*$ is the noise-to-signal ratio, defined to measure the quality of surrogate model relative to the algorithm's step size, $c_{\mu/\mu, \lambda}$ is the $(\mu/\mu, \lambda)$ -progress coefficient derived by Arnold and Beyer [1] that follows

$$c_{\mu/\mu, \lambda} = \frac{\lambda - \mu}{2\pi} \left(\frac{\lambda}{\mu} \right) \int_{-\infty}^{\infty} e^{-x^2} [\Phi(x)]^{\lambda-\mu-1} [1 - \Phi(x)]^{\mu-1} dx,\tag{7}$$

where Φ^{-1} is the inverse function of Φ , the normal cumulative distribution function. The integral can be solve numerically.

To obtain the opt. expected fitness gain η_{opt} and its corresponding opt. normalized step size σ_{opt}^* , we take derivative of equation (6) over σ^* and get the following

$$\sigma_{opt}^* = \frac{\mu c_{\mu/\mu, \lambda}}{\sqrt{1 + \vartheta^2}}\tag{8}$$

$$\eta_{opt} = \frac{\sigma_{opt}^* c_{\mu/\mu, \lambda}}{\sqrt{1 + \vartheta^2}} - \frac{(\sigma_{opt}^*)^2}{2\mu}\tag{9}$$

The expected fitness gain is normalized in terms of the population size λ for easy comparison. The normalized fitness gain against the normalized step size for $(\mu/\mu, \lambda)$ -ES with population size $\lambda = 10, 20, 40$ corresponding $\mu = 3, 5, 10$ are plotted in 1 from left to right respectively. The line shows the result obtained from Eqs. (6) (7). The dots represent the

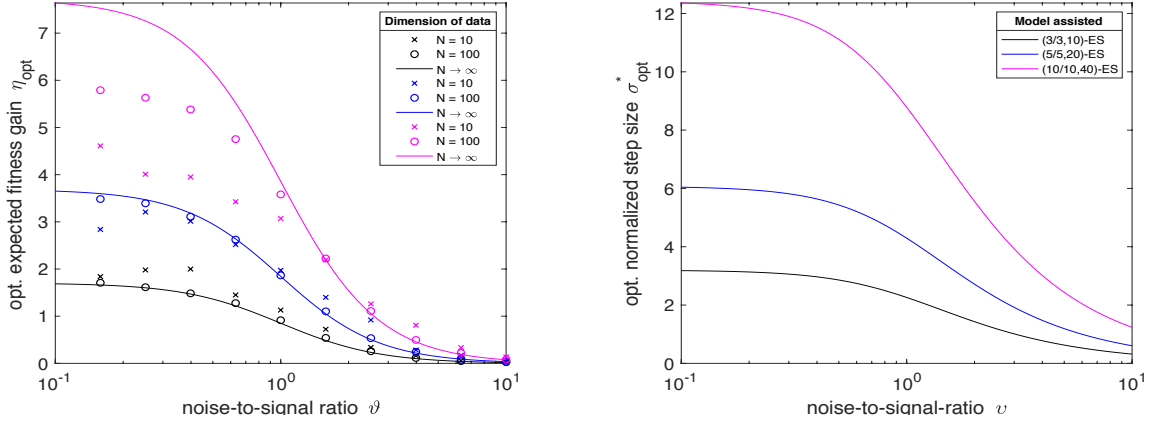


Fig. 2. Opt. expected fitness gain and corresponding opt. normalized step size of the surrogate model assisted $(\mu/\mu, \lambda)$ -ES plotted against the noise-to-signal ratio. The line and dots with colour black, blue green represent (3/3, 10)-ES, (3/3, 10)-ES, (3/3, 10)-ES. The solid line represents the results obtained analytically when $n \rightarrow \infty$.

experimental result for unbiased Gaussian surrogate error for $n \in \{10, 100\}$ obtained by averaging 100 runs. The result obtained for $n \rightarrow \infty$ are considered to be cases with a large normalized step size with very small noise to signal ratio.

It can be inferred from Fig. 1, for a fixed population size, the expected fitness gain decreases with an increasing noise-to-signal-ratio. When $\vartheta \rightarrow \infty$, the surrogate model becomes useless and the strategy becomes a random search. For moderate noise-to-signal ratio ϑ , the surrogate model assisted algorithm can achieve much larger value for expected fitness gain at a larger normalized step size. When $\vartheta = 1$, the maximal expected fitness gain achievable for (3/3, 10)-ES, (5/5, 20)-ES and (10/10, 40)-ES are 0.8507, 1.841, 3.808 with $\sigma^* = 2.254, 4.251, 8.738$ respectively. Compared with the result of the surrogate assisted (1+1)-ES [17] where maximal fitness gain is 0.548 achieved at $\sigma^* = 1.905$, $(\mu/\mu, \lambda)$ -ES does benefit from using a larger population from the analysis. For $\vartheta = 0$ (the surrogate models the objective function exactly), from equation (8) we can obtain the maximal expected fitness gain is achieved at $\sigma_{opt}^* = \mu c_{\mu/\mu, \lambda}$ with value $\eta_{opt} = \mu(c_{\mu/\mu, \lambda})^2/2$. Even if this indicates the potential benefit the strategy may gain with a growing population, it is important to note the analytical results derived when $n \rightarrow \infty$ is an approximation for the finite-dimensional case. Fig. 2 shows the relation of optimal expected fitness gain and the corresponding optimal normalized step size over noise-to-signal ratio derived analytically in the limit of $n \rightarrow \infty$ for three different population sizes. The optimal expected fitness gain is also measured experimentally for $n \in \{10, 100\}$. **how to calculate the speed up?** For a finite-dimension, the speed-up achieved with surrogate model assistance for small noise-to-signal ratio appears to be between ...

Compared the result obtained by the surrogate assisted (1+1)-ES (Fig 1. [17]), there is indeed a
there is a significant increase in expected fitness gain as the population size λ increases, the

4 STEP SIZE ADAPTATION

4.1 Cumulative step size adaptation

Even though the analysis in Section 3 suggests a potential better performance for the surrogate-assisted $(\mu/\mu, \lambda)$ -ES. There is no guarantee the step size of the strategy can be properly adapted and further the analysis is very inaccurate in

Algorithm 1 A Surrogate Assisted $(\mu/\mu, \lambda)$ -ES

```
1:  $c \leftarrow \frac{\mu+2}{n+\mu+5}$ 
2:  $d \leftarrow 1 + 2\max(0, \sqrt{\frac{\mu-1}{n+1}} - 1)$ 
3:  $p \leftarrow 0$ 
4: while not terminate() do
5:   for  $i = 1, 2, \dots, \lambda$  do
6:     Generate standard normally distributed  $z_i \in \mathbb{R}^N$ 
7:      $y_i \leftarrow x + \sigma z_i$ 
8:     Evaluate  $y_i$  using the surrogate model, yielding  $f_\epsilon(y_i)$ 
9:   end for
10:   $z = \frac{1}{\mu} \sum_{i=1}^{\mu} z_{i;\lambda}$ 
11:   $y = x + \sigma z$ 
12:  Evaluate  $y$  using true objective function, yielding  $f(y)$ 
13:  Update surrogate model
14:   $s \leftarrow (1 - c)s + \sqrt{c(2 - c)\mu}z$ 
15:   $\sigma \leftarrow \sigma \times \exp\left(\frac{c}{d} \frac{\|X\|}{E\|N(0, I)\|} - 1\right)$ 
16: end while
```

terms of finite dimension. In this section we experiemnt the surroagted model assisted $(\mu/\mu, \lambda)$ -ES using the cumulative step size adaptation described in Section 2.2 and exploit the potential insight it may offer. The strategy is evaluated by using a Gaussian Process based surrogate model replacing the simple model that simulates the surrogate behaviour in Section 3. Several test functions are used for testing the strategy.

Here, we use the well established parameters from Hansen’s CMA tutorial [10] that follows

$$\begin{cases} c = (\mu + 2)/(N + \mu + 5) \\ d = 1 + 2 \max\left(0, \sqrt{(\mu - 1)/(N + 1) - 1}\right) + c. \end{cases} \quad (10)$$

The one signle iteration for the surrogate model assisted $(\mu/\mu, \lambda)$ -ES is shown in Alg. 1.

Five ten-dimensional test problems are used to test if the step size of the strategy has been appropriately adapted, namely sphere functions $f(x) = (x^T x)^{\alpha/2}$ for $\alpha = \{1, 2, 3\}$ referred to as linear, quadratic and cubic spheres, $f(x) = \sum_{i=1}^n (\sum_{j=1}^i x_j)^2$ (i.e. a convex quadratic function with condition number of the Hessian approximately equal to 175.1) referred to as Schwefel’s Problem 1.2 [22]) and quartic function [17] defined as $f(x) = \sum_{i=1}^{n-1} [\beta(x_{i+1} - x_i^2)^2 + (1 - x_i)^2]$ where $\beta = 1$. The quartic function becomes the Rosenbrock function when the condition number of the Hessian at the optimier exceeds 3,500, making it very hard to find the global optima without adapting the shape of mutation distribution. We use the quartic function in the context with $\beta = 1$ and condition number of the Hessian at the optimizer equals to 49.0. The value of global optima for all test functiosn is zero. For each test problem, 1000 runs are conducted both for surrogate assisted $(1 + 1)$ -ES and surrogate assisted $(\mu/\mu, \lambda)$ -ES where a parental population size $\lambda = 10, 20, 40$ with $\mu = \lceil \lambda/4 \rceil$. For surrogate model, we use Gaussin process. We use sward exponential kernel and the length scale paramter in the kernel is set proportional to the square of the dimension and the step size of the Evolution strategy. For simplicity, the length scale is $8\sigma\sqrt{n}$. The Gaussian process kernel is constructed using a trainijng size of 40. The training set consists of the most recent 40 candidate so that the surrogate model approximates the local landscape of the objective function. All runs are initialized with starting point sampled from a Gaussin distribution with zero mean

Table 1. Median test results.

Test functions	Median number of objective function calls (with model assistance)			
	(1 + 1)-ES	(3/3, 10)-ES	(5/5, 20)-ES	(10/10, 40)-ES
linear sphere	505	754	689	755
quadratic sphere	214	310	245	228
cubic sphere	202	274	250	254
Schwefel's function	1496	$+\infty$	$+\infty$	$+\infty$
quartic function	1244	1006	750	662

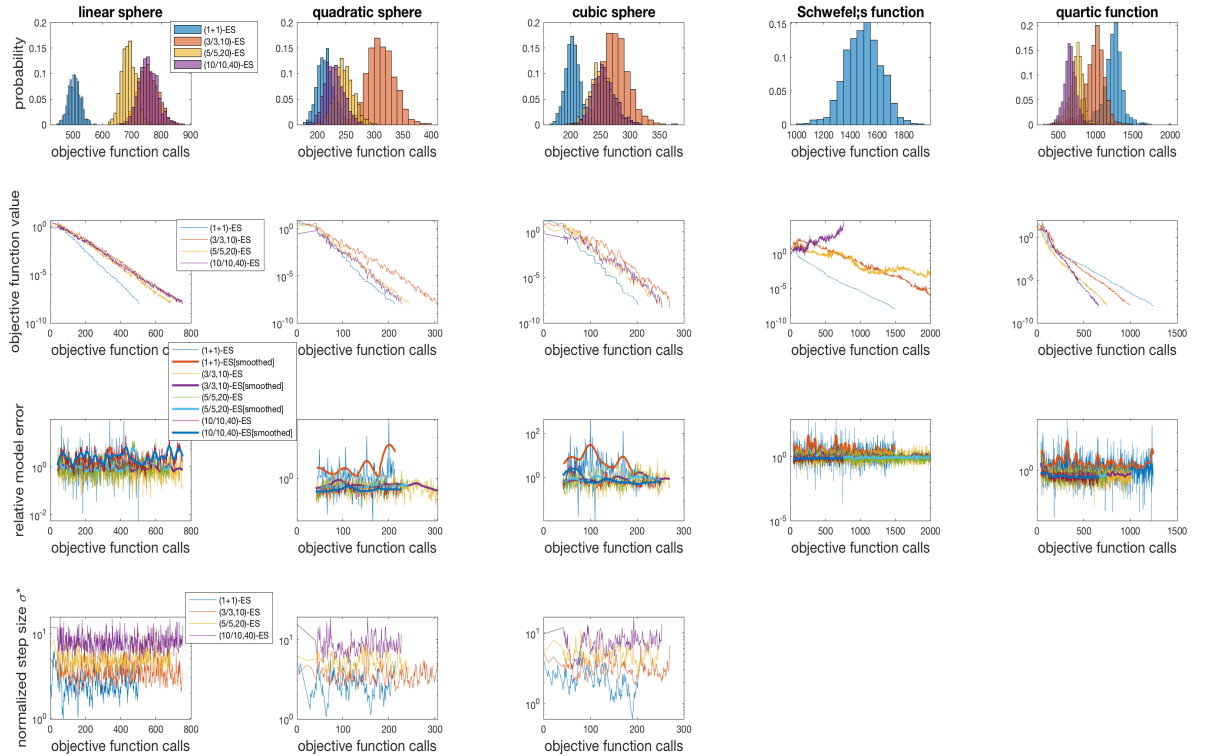


Fig. 3. Result obtained by adapting step size using CSA. Top row: Histogram showing the number of objective function calls needed to solve the five test problems. Second row: Convergence graphs for median runs. Third row: Relative model error obtained in median runs. Last row: normalized step size measured in median runs. **legend looks messy is there a way out?**, **relative model error for (1+1)-ES different**

and unit covariance matrix and initial step size $\sigma_0 = 1$. The termination criteria is defined as one solution achieves objective function value below 10^{-8} .

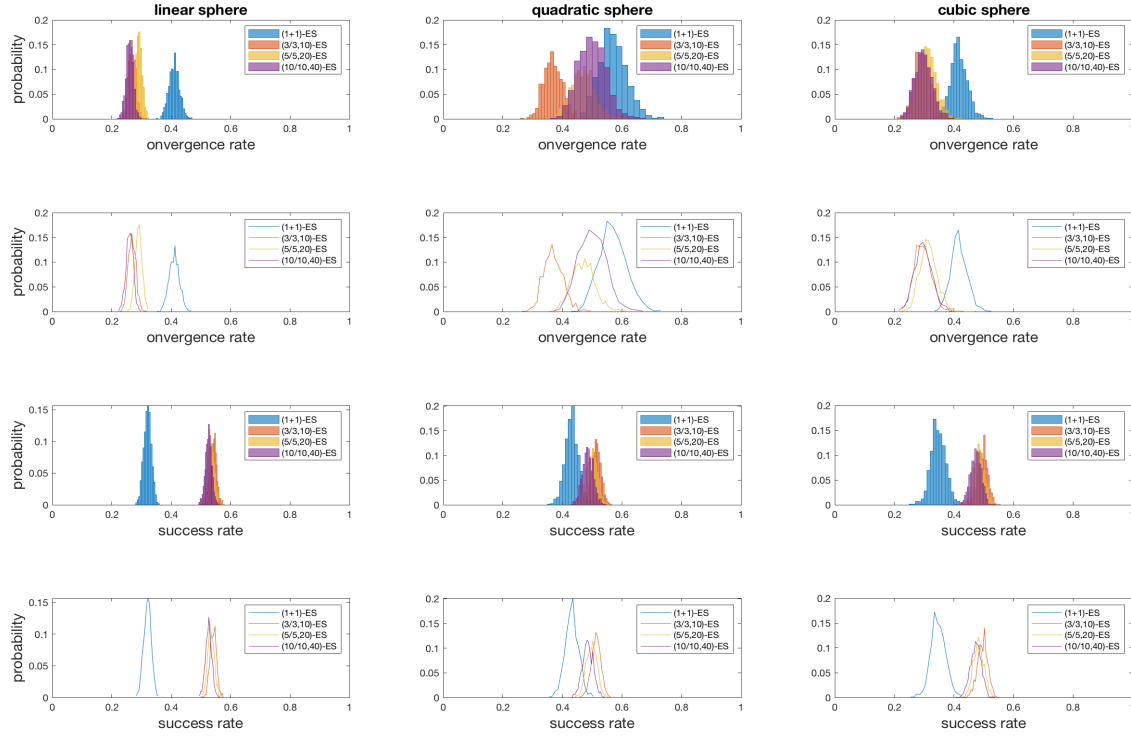


Fig. 4. Result obtained by adapting step size using CSA. The first two rows show the normalized convergence rate for each run plotted in histogram and normalized probability density function (pdf) respectively. The last two rows represent the success rate (proportion of good step size in each run) plotted in histogram and pdf respectively.

Histogram showing the number of objective function calls needed to solve the test problems within the required accuracy are represented in the first row of 3, the median objective function calls for each test problem is shown in Table 1. The result of Arash and Dirk [17] using surrogate assisted (1+1)-ES is also included for comparison. The results of surrogate assisted $(\mu/\mu, \lambda)$ -ES do not match the performance of surrogate assisted (1+1)-ES. The speed-up is defined as the median number of objective function evaluations used by the surrogate assisted (1+1)-ES [17] divided by the surrogate assisted $(\mu/\mu, \lambda)$ -ES. Despite achieving a speed up from 1.2 to 1.9 for quartic function, the surrogate assisted $(\mu/\mu, \lambda)$ -ES performs worse on sphere functions and even does not converge in Schwefel's function. There is a trend in quadratic sphere and quartic function that the performance improves with a growing parental population, the number of objective function evaluations needed to solve linear sphere even increases after $\lambda > 20$.

The second row of Fig. 3 shows the convergence graphs for the median runs. Linear convergence are achieved for all test functions despite the Schwefel's function using surrogate assisted $(\mu/\mu, \lambda)$ -ES, interestingly, using a larger population does not help achieve a better convergence rate, but instead, makes the strategy diverge. Relative model error for the median runs is shown in the third row of the figure, defined as $\|f(y) - f_\epsilon(y)\|/\|f(y) - f(x)\|$ where x is the parent and y the offspring candidate solution for (1+1)-ES and $\text{var}(f(y) - f_\epsilon(y))/\text{var}(f(y))$, the variance of the difference between the surrogate estimate of λ candidate solutions and their true objective function values divided by

Table 2. Median test results.

Test functions	Median number of objective function calls (with model assistance)			
	(1 + 1)-ES	(3/3, 10)-ES	(5/5, 20)-ES	(10/10, 40)-ES
linear sphere	505	369	315	322
quadratic sphere	214	212	162	146
cubic sphere	203	213	180	177
Schwefel's function	1496	$+\infty$	1205	1067
quartic function	1244	1505	987	797

the variance of the variance of the true objective function values of λ candidate solutions for $(\mu/\mu, \lambda)$ -ES. The relative model error is smoothed logarithmically by convolution with a Gaussian kernel with window size 40 that is represented as the bold line in the centre of the plots. This can be interpreted as the a relative constant noise-to-signal ratio. The relative model error for all surrogate assisted ES in this context is approximately 1 and according to the analysis in Section 3 should give a much larger speed up especially given a larger population. This may give indication that the step size is not appropriately adapted. The bottom row shows the normalized step size $\sigma^* = N\sigma/R$ for three sphere functions, where N, R are the dimension of data and distance to optimal respectively is the dimension. It coincides with the knowledge that using a population in offspring generation is possible for larger step size but the potential improvement is still yet clear.

There is a big gap between experimental result and analytical result in Section 3, and the relation between the expected fitness gain and parental population size. To understand what

Firstly, the step size is not appropriately adapted using CSA. The bias of the Gaussian process surrogate can be another problem and we will discuss these further in future work.

I think I've got an idea, we could finish this part tonight and we could discuss tomorrow

4.2 Cumulative step size adaptation with emergency

From Fig. 4, the success rate for all test functions are approximately 0.48, the strategy makes a bad step every other step. It comes natural to ask, how much we are to benefit if we can avoid or simply not take those bad steps.

Recent papers in surrogate model assisted ES consider (1+1)-ES, the step size of the strategy is successfully adapted using the 1/5-rule [1]. Then we probably can apply a similar criteria when encounter a bad step size.

Propose step size adaptation in terms of emergency.

5 CONCLUSIONS

In this paper, We proposed a local surrogate-assisted $(\mu/\mu, \lambda) + (\mu/\mu, \lambda)$ -ES. The strategy uses a local surrogate model to optimize the candidate solution obtained in each iteration. The performance is analyzed by adding different levels of Gaussian distributed noise and applying the strategy to sphere functions.

Algorithm 2 Cumulative Step Size Adaptation with Emergency

```
1:  $c \leftarrow \frac{\mu+2}{n+\mu+5}$ 
2:  $d \leftarrow 1 + 2\max(0, \sqrt{\frac{\mu-1}{n+1}} - 1)$ 
3:  $p \leftarrow 0$ 
4:  $D \leftarrow 0.68$ 
5: while not terminate() do
6:   for  $i = 1, 2, \dots, \lambda$  do
7:     Generate standard normally distributed  $z_i \in \mathbb{R}^N$ 
8:      $y_i \leftarrow x + \sigma z_i$ 
9:     Evaluate  $y_i$  using the surrogate model, yielding  $\hat{f}(y_i)$ 
10:   end for
11:    $z = \frac{1}{\mu} \sum_{i=1}^{\mu} z_i; \lambda$ 
12:    $y = x + \sigma x$ 
13:   Evaluate  $y$  using true objective function, yielding  $f(y)$ 
14:   Update surrogate model
15:   if  $f(x) < f(y)$  (Emergency) then
16:      $\sigma \leftarrow \sigma D$ 
17:   else
18:      $s \leftarrow (1 - c)s + \sqrt{c(2 - c)\mu z}$ 
19:      $\sigma \leftarrow \sigma \times \exp\left(\frac{c}{d} \frac{\|X\|}{E\|N(0, I)\|} - 1\right)$ 
20:   end if
21: end while
```

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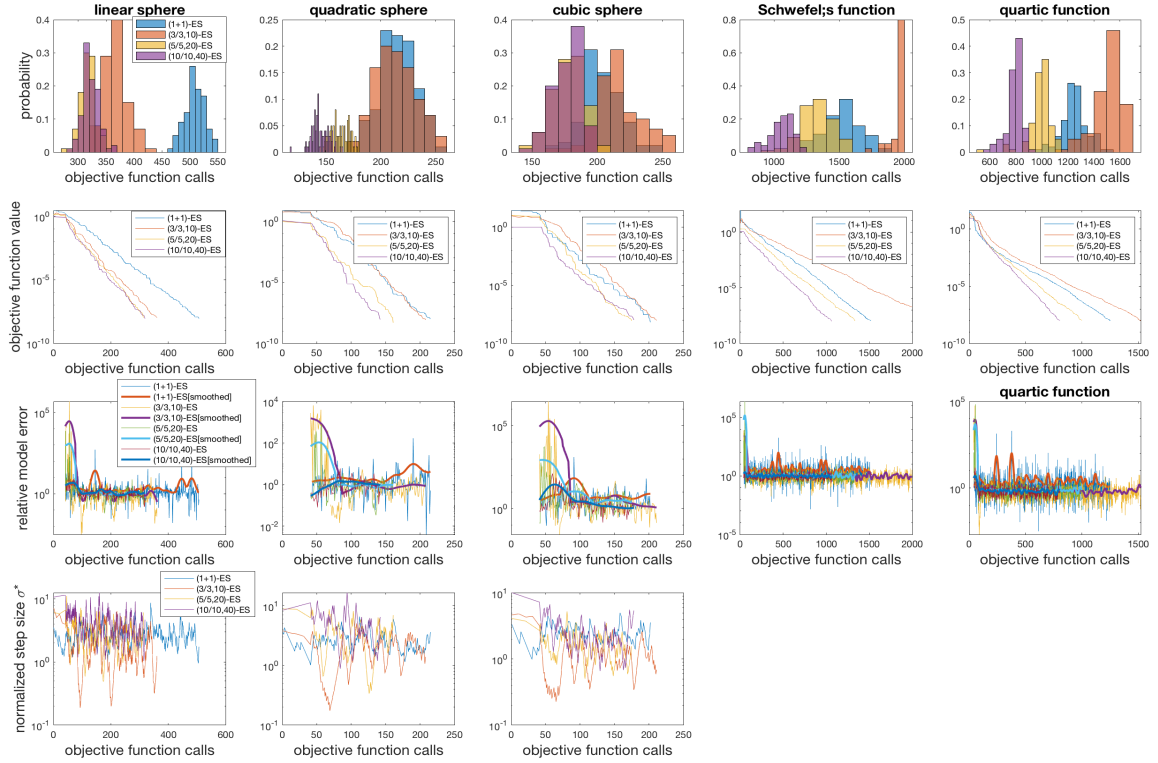


Fig. 5. Result obtained by adapting step size using CSA with emergency. Top row: Histogram showing the number of objective function calls needed to solve the five test problems. Second row: Convergence graphs for median runs. Third row: Relative model error obtained in median runs. Last row: normalized step size measured in median runs.

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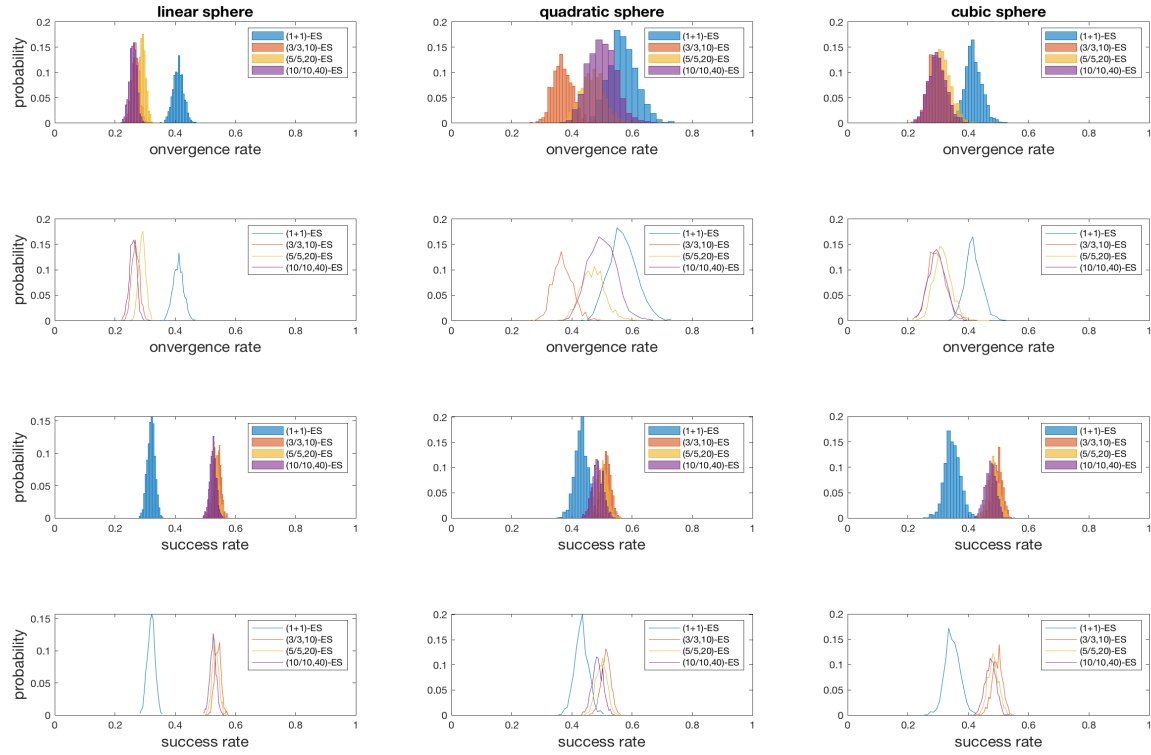


Fig. 6. Result obtained by adapting step size using CSA with emergency. The first two rows show the normalized convergence rate for each run plotted in histogram and normalized probability density function (pdf) respectively. The last two rows represent the success rate (proportion of good step size in each run) plotted in histogram and pdf respectively.

is a problem but will be solved as more texts are added