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Pick a Color MARIA: Adaptive Sampling Enables the Rapid Identification of Complex Perovskite Nanocrystal Compositions with Defined Emission Characteristics

Leonard Bezinge,[†] Richard M. Maceiczyk,[†] Ioannis Lignos,[†]

Maksym V. Kovalenko[‡§]* and Andrew J. deMello[†]*

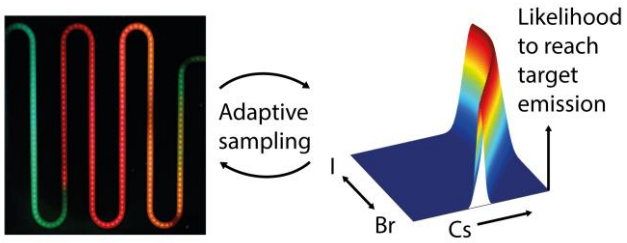
† Institute for Chemical and Bioengineering, Department of Chemistry and Applied Biosciences, ETH Zürich, Vladimir-Prelog-Weg 1, 8093 Zürich, Switzerland.

‡ Institute of Inorganic Chemistry, Department of Chemistry and Applied Biosciences, ETH Zürich, Vladimir-Prelog-Weg 1, 8093 Zürich, Switzerland.

§ Laboratory for Thin Films and Photovoltaics, Empa - Swiss Federal Laboratories for Materials Science and Technology, Überlandstrasse 129, 8600 Dübendorf, Switzerland.

* andrew.demello@chem.ethz.ch

* mvkovalenko@ethz.ch



Abstract

Recent advances in the development of hybrid organic-inorganic lead halide perovskite (LHP) nanocrystals (NCs) have demonstrated their versatility and potential application in photovoltaics and as light sources through compositional tuning of optical properties. That said, due to their compositional complexity, the targeted synthesis of mixed-cation and/or mixed-halide LHP NCs still represents an immense challenge for traditional batch-scale chemistry. To address this limitation, we herein report the integration of a high-throughput segmented-flow microfluidic reactor and self-optimizing algorithm for the synthesis of NCs with defined emission properties. The algorithm, named Multiparametric Automated Regression Kriging Interpolation and Adaptive sampling (MARIA), iteratively computes optimal sampling points at each stage of an experimental sequence to reach a target emission peak wavelength based on spectroscopic measurements. We demonstrate the efficacy of the method through the synthesis of multinary LHP NCs - $(Cs/FA)Pb(I/Br)_3$ (FA = formamidinium) and $(Rb/Cs/FA)Pb(I/Br)_3$ NCs - using MARIA to rapidly identify reagent

concentrations that yield user-defined photoluminescence peak wavelengths in the green-red spectral region. The procedure returns a robust model around a target output in far fewer measurements than systematic screening of parametric space and additionally enables the prediction of other spectral properties, such as, full-width at half-maximum and intensity, for conditions yielding NCs with similar emission peak wavelength.

Keywords: Perovskites; Quantum dots; Nanocrystals; Microfluidics; Kriging; Optimization

Introduction

Lead halide perovskite (LHP) nanocrystals (NCs), first reported just a few years ago[1,2] are an important class of colloidal semiconductor NCs with attractive optoelectronic properties[3–5] and potential applications in lasers,[6–11] light-emitting devices (LEDs),[12–16] fast single-photon sources,[17,18] or as photosensitizers or absorbers in photovoltaic cells[19–22] and photodetectors.[23] LHPs, with the general formula $APbX_3$, consist of an organic or inorganic A-site cation (commonly methylammonium (MA^+), formamidinium (FA^+), caesium (Cs^+) or a mixture thereof) residing within a 12-fold coordinated site formed by [PbX_6] octahedra, where X is Cl^-, Br^-, I^- or a mixture thereof. The ability of hybrid LHP materials to form solid solutions of mixed cations and anions within a single homogeneous phase enables broad compositional tuning of optical properties. A large variety of LHP nanocrystal compositions have been reported and include, but are not limited to, $MAPbX_3$,[1,12,24] $FAPbX_3$,[25–28] $CsPbX_3$,[2,29,30] doped $CsPbX_3$ (Mn^{2+}, Sn^{2+}, Cd^{2+}, Zn^{2+} or Bi^{3+} as dopant),[31–35] and $(Cs/FA)PbI_3$ NCs.[27] An increase in compositional complexity is often motivated by a desire to improve performance and mitigate stability issues, which remain the primary challenge hindering the implementation of LHPs in next-generation solar cells and other optoelectronic devices. In this respect, the introduction of mixed cations or interstitial defects thermodynamically stabilizes the photoactive phase[36] and even decreases the sensitivity of LHPs to light, moisture and temperature.[37–39] Such multinary LHP, in the form of thin films, have been the subject of intense investigation for application in solar cells, with materials such as $(Cs/MA/FA)Pb(Br/I)_3$ and $(Rb/Cs/MA/FA)PbI_3$ demonstrating remarkable photoconversion efficiencies (above 20%) over timespans of several weeks.[37,38]

Computer simulations and empirical theories (such as the Goldschmidt tolerance factor[40,41]) have also been used to evaluate the feasibility and consequences of introducing various cations into the LHP crystal lattice, and confirm the empirical observation that complex, multinary perovskites are often superior to simpler compositions.[27,42–44] The synthesis of perovskite NC populations with

defined and homogeneous composition, size and dimensionality is enormously challenging since these properties are highly sensitive to synthetic conditions such as the type and concentration of both precursors and surfactants.[26,45] Understanding of the formation mechanism of LHP NCs is limited by practical hurdles in controlling an in-situ monitoring of these reactions due to short reaction times (on the order of a few seconds) and fast ion exchange kinetics, even at room temperature.[27–29] Indeed, in the case of complex LHPs, empiric synthesis optimization requires a very large number of experiments, inaccessible with the flask-based syntheses. In such an endeavour, segmented-flow microfluidic reactors, equipped with real-time optical detectors, can tremendously accelerate the parametric screening, whilst consuming miniscule amounts of reagents.[28,29,46–54] That said, for the multidimensional parameter spaces encountered in LHP systems the complete mapping of parameter space with incremental changes in all experimental parameters and containing all parameter combinations is still unfeasible, and thus a more intelligent, target-oriented approach/algorithm would strongly benefit the exploration of novel and compositionally complex NCs.[55–60]

In the context of LHPs, the primary defining characteristic of interest is the peak emission peak wavelength. Herein, we use a Kriging-based algorithm to target a specific photoluminescence (PL) emission wavelength and find all possible experimental conditions yielding NCs with the desired emission, initially neglecting other spectral properties. For a given class of complex LHP NCs, similar PL peak wavelengths might originate from a multitude of combinations of compositions, sizes or even NC shapes; with two latest parameters influencing the emission energy by quantum-size effects. However, these various NCs, although exhibiting same PL peak wavelengths, might exhibit vastly different PL quantum yield (PL QY), PL emission linewidth and, particularly important for LHP NCs, stability. The selection of promising material candidates for performance tests and offline characterization relies on the identification of trends and patterns in the functional dependence of the spectral properties.[61] Initially developed for geological applications in the 1960s, Kriging metamodels have been extensively used in deterministic or noisy computer experiments.[62,63] They define a family of non-parametric interpolation methods used in global optimization problems and recently also as prediction tools for the reaction outcomes of photoluminescent nanomaterials.[52,64–66]

In the current work, we present an efficient goal-seeking algorithm named Multiparametric Automated Regression Kriging Interpolation and Adaptive sampling (MARIA) which identifies future reaction conditions based on previous measurements. In conjunction with a microfluidic reactor, MARIA forms a self-optimizing system that autonomously explores conditions of interest. The primary goal of the developed platform is to rapidly return an accurate model identifying reaction conditions that yield NCs with desired optical properties. We demonstrate the efficacy of our method

for the synthesis of (Cs/FA)Pb(Br/I)$_3$ NCs with controlled PL emission maxima at either 560, 620 or 680 nm. We further test the accuracy of the resulting model for 680 nm-emitting NCs and compare the synthesized NCs in terms of FWHM and PL intensity. Finally, we extend the optimization to three-dimensional parameter space for the synthesis of complex (Rb/Cs/FA)Pb(Br/I)$_3$ NCs with PL peak at 600 nm. This work will guide future experimental efforts on a large scale (typical reaction flasks), by suggesting a set of synthesis protocols for designated emission ranges. Once these syntheses will be adapted by the batch reactors, the obtained NCs will be compared in terms of their stability and durability.

Adaptive Sampling Algorithm

MARIA provides a response surface from data observed at previously sampled points within a parameter space as well as a method to select the next point to be sampled. We choose Kriging as basis for MARIA because it has already been introduced in the context of complex reaction systems and other black-box systems.[52,64] It is well-suited as a response surface model for complex, unknown systems as it does not require any assumptions about the functional dependence of output parameters on experimental conditions. Moreover, in addition to a predictor value, Kriging supplies the variance corresponding to each prediction, which can subsequently serve as a tool to guide sampling. Commonly, a two-step approach is adopted in global optimization problems,[66] with Kriging predictors being first computed throughout parameter space and then the probability of improving the current minimum being evaluated to determine the optimal sampling position. Kriging-based goal seeking methods, in contrast, have received very little attention.[65] Herein, we propose a one-step approach that directly assesses the likelihood that any experimental condition will yield a predefined target wavelength.

We note that in the following we use bold lower-case letters for (column) vectors (with the unit vector denoted as $\mathbf{1}$) and bold upper-case letters for matrices ($\mathbf{I}$ being the identity matrix). Superscript T indicates the transpose of a vector/matrix. Regular font symbols and letters refer to scalar functions, variables or constants. A basic assumption of Kriging is that observables y at positions $\mathbf{x}$ within the parameter space are realizations of a stochastic process Y comprising a model constant β and local deviations $Z(\mathbf{x})$:[64,67]

$$Y(\mathbf{x}) = \beta + Z(\mathbf{x}) \#(1)$$

In addition, we postulate that two stochastic variables $Y(\mathbf{x}_i)$ and $Y(\mathbf{x}_j)$ at positions $\mathbf{x}_i$ and $\mathbf{x}_j$ in a d-dimensional parameter space are correlated and their degree of correlation quantified by the

function $\mathrm{Corr}\left(Y(\mathbf{x}_i), Y(\mathbf{x}_j)\right)$, which depends on the weighted "distance" between the two positions according to:[64]

$$\mathrm{Corr}\left(Y(\mathbf{x}_i), Y(\mathbf{x}_j)\right) = \exp\left(-\sum_{\ell=1}^{d} \theta_\ell \left|\mathbf{x}_i - \mathbf{x}_j\right|^{p_\ell}\right) \#(2)$$

The exponents p_ℓ are an expression of the smoothness of the data, with $p_\ell = 2$ corresponding to a smooth and continuous response surface, as is expected for our system. In fact, the choice of $p_\ell = 2$ results in a model based on a Gaussian kernel with variance $1/\theta_\ell$.[63] The coefficients θ_ℓ determine how rapidly the correlation between two variables decreases with distance in each dimension, which can be seen as a measure of dimensional activity. Inactive dimensions (those with rapidly decreasing correlation) have high values of θ_ℓ, whereas active dimensions require small values of θ_ℓ to capture the long-range correlation of function values.[64] To generate a model from these assumptions, Kriging involves the search of a random process that best describes a set of n measured samples, $\mathbf{y} = [y(\mathbf{x}_1), \ldots, y(\mathbf{x}_n)]^{\mathrm{T}}$.[62] Following the classical derivation of Kriging, we consider a vector of random variables $\mathbf{Y} = [Y(\mathbf{x}_1), \ldots, Y(\mathbf{x}_n)]^{\mathrm{T}}$ at sampled positions $\mathbf{x}_1$, $\mathbf{x}_2$,…, $\mathbf{x}_n$, with a mean $\mathbf{1}\mu$ and a covariance matrix $\mathrm{Cov}(\mathbf{Y}) = \sigma^2\mathbf{R}$, where σ is the standard deviation and $\mathbf{R}$ the correlation matrix with elements $R_{ij} = \mathrm{Corr}\left(Y(\mathbf{x}_i), Y(\mathbf{x}_j)\right)$.[67] This definition of covariance implies that a variable is perfectly correlated with itself according to Equation 2 ($R_{ii} = 1$), which forces the response surface to include measured values without considering noise or experimental error. In the context of nanomaterial synthesis, we expect that the optical properties of NC populations will be subject to noise emanating from limited measurement precision and reaction control. In order to incorporate this into the model, we allow regression of experimental data by adding a regression parameter Λ to the diagonal element of the correlation matrix R_{ij}, thus giving rise to a new covariance matrix $\mathrm{Cov}'(\mathbf{Y}) = \sigma^2(\mathbf{R} + \Lambda\,\mathbf{I})$.[63] An optimal model constitutes a combination of parameters θ_i and Λ constructing a stochastic process that most likely describes the measured data. We accomplish this by maximizing the likelihood to generate the set of observables $\mathbf{y}$ from the stochastic process previously described to obtain the so-called best linear unbiased predictor (BLUP) $\hat{y}(\mathbf{x}^*)$ and its associated variance $\hat{s}^2(\mathbf{x}^*)$ (Derivation provided in the Supporting Information):[67]

$$\hat{y}(\mathbf{x}^*) = \hat{\mu} + \mathbf{r}(\mathbf{x}^*)^{\mathrm{T}}(\mathbf{R} + \Lambda\mathbf{I})^{-1}(\mathbf{y} - \mathbf{1}\hat{\mu}) \#(3)$$

Figure 1a shows the effect of parameter θ on the function predictor and the calculated model likelihood for $\Lambda = 0$. High values of θ result in a predictor that is weakly influenced by the data with localized deviations from the model mean $\hat{\mu}$. In contrast, for low values of θ, predictor values are highly correlated to the data over long distances. There exists an optimal value of θ for which the

correlation function most likely describes the measured values, which MARIA automatically chooses. If we consider a system subject to noise or experimental error, the case $\Lambda = 0$ returns a distorted response surface as it is forced to go through every sample point ($\hat{s}(\mathbf{x}_i) = 0$). In contrast, regressing the data ($\Lambda > 0$) better captures the shape of the underlying function (Figure 1b). MARIA returns a response surface (with parameters θ and Λ) that maximizes the likelihood of generating the observables. This combination of parameters is inherent to the measured data and independent of the location at which a prediction is made.

The next step in building the optimization algorithm is to determine a way to select subsequent points for sampling. Recalling that Kriging models assume that observables are realizations of a stochastic process, immediately enables us to statistically evaluate predictions. Outputs of the BLUP at reaction conditions $\mathbf{x}^*$ correspond to a probability density function (PDF) of a Gaussian distribution, with mean $\hat{y}(\mathbf{x}^*)$ and variance $\hat{s}^2(\mathbf{x}^*)$.[64] Integrating the PDF returns the probability of measuring an observable at the point $\mathbf{x}^*$ within the range of integration. By calculating the probability to improve the current minimum, $P(y < y_{\min})$ at every coordinate this feature can be used directly in global optimization problems, where the goal is minimization of an objective function (Figure 1c).[65] In the case of a goal-seeking problem, the system is commonly transformed into an optimization problem by transformation of the objective function, e.g. minimize $(y - y^*)^2 + v$ for a target value of y^* with minimal secondary property v (*e.g.* FWHM, inverse of intensity).[59] However, two concerns arise from this approach. First, it is up to the user to determine the weights of each property in the objective function which is arbitrary and might vary depending on the materials and their applications.[68] Second, these algorithms return a single optimal point. However, if a nanomaterial is unstable or difficult to use for device fabrication, the optimization will fall short and the user must redefine boundaries that exclude the current material and allow identification of a new candidate. For LHPs, material stability has been the primary hurdle in the development of new materials and has been shown to be strongly dependent on both composition and doping.[37,38,69] In this respect, a target-oriented approach returning all conditions that yield the desired emission is preferable and eventually provides a basis for comparing optical properties (*e.g.* FWHM, intensity) of materials with similar emission maximum. Jones *et al.*[65] describe a Kriging-based target-oriented approach by adding an hypothetical data point at position $\mathbf{x}^*$ with value y^* (target output) to the set of observables. In a subsequent step, parameters θ_ℓ and Λ are computed via the maximum likelihood evaluation and the resulting likelihood measures the credibility of the hypothesis. This procedure repeats at every point of interest before selecting the point with the highest credibility, rendering this approach computationally intensive and impractical for high-dimensionality systems. To address this limitation, we propose a streamlined approach, where first the coefficients θ_ℓ and Λ are

optimized using previously sampled data. The algorithm then computes the likelihood of any position $\mathbf{x}^*$ resulting in the targeted value y^* under the hypothesis that $\hat{y}(\mathbf{x}^*) = y^*$. To illustrate this concept, Figure 1d displays the likelihood of a Kriging model reaching two different target values y_1^* and y_2^*. The next measurement condition is chosen at the point with the highest likelihood. Our approach exhibits several key advantages: first, it is a one-step approach and does not require the computation of the full response surface at each iteration (likelihood estimation only requires parameters θ_ℓ and Λ, without computing a BLUP), considerably speeding up computation times, especially for high-dimensionality systems. Second, no transformation of the system through an objective function is needed, which renders the analysis of outputs and comparison to experimental data simpler and more intuitive.

Concerning the numerical implementation of the algorithm, parameter space is discretized in a fine grid, i.e. with the smallest physically meaningful and experimentally feasible spacing between neighbouring parameter combinations. Each discrete position corresponds to a specific experimental condition and thus a purposeful grid spacing will reflect the limited accuracy of the experimental set up. The interpolated values and likelihood of reaching the target are evaluated at every point of the grid. The full MARIA and adaptive sampling procedure can be summarized as follows (Figure 2): starting from an initial set of measurements, the adaptive sampling algorithm fits a Kriging model and computes optimal parameters for subsequent sampling with the highest likelihood of reaching a defined target value. The process is repeated until the end criterion is met (or in our case a predefined number of iterations).

The quality of the final model is assessed by "leave-one-out" cross-validation, which evaluates the sensitivity of the model to lost information. The standardized cross-validated residuals E_i are given by:[64]

$$E_\mathrm{i} = \frac{y_\mathrm{i}(\mathbf{x}_i) - \hat{y}_{-i}(\mathbf{x}_i)}{\hat{s}_{-i}(\mathbf{x}_i)} \#(4)$$

Here, $y_\mathrm{i}(\mathbf{x}_\mathrm{i})$ is the measured value at position $\mathbf{x}_i$, and $\hat{y}_{-i}(\mathbf{x}_i)$ and $\hat{s}_{-i}(\mathbf{x}_i)$ are Kriging predictions obtained after removing the i-th measurement point. The first and second moments Q_1 and Q_2 of the standardized residuals provide valuable information about the mean and variance of the distribution of residuals: $Q_1 = \frac{1}{n}\sum_{i=1}^{n} E_i$ and $Q_2 = \frac{1}{n}\sum_{i=1}^{n} E_i^2$.[52,70] Ideally, the cross-validated residuals are consistent with the stochastic output of the BLUP, i.e. normally distributed around the predictor $\hat{y}$ with variance $\hat{s}^2$, with the moments taking values of $Q_1 = 0$ and $Q_2 = 1$.

Results and Discussion

We allow MARIA to conduct experiments in an automatic and independent fashion by interfacing the algorithm with an automated microfluidic platform equipped with an online fluorescence detector (see Supporting Information for details).[49] Segmented-flow capillary reactors provide an ideal platform for the high-throughput synthesis of (Cs/FA)Pb(Br/I)$_3$ nanocrystals, with real-time acquisition of PL spectra enabling fully automated operation (Figure S1).[28,29,54] A schematic representation of the setup is depicted in Figure 3a. Specifically, we achieve full control of caesium doping and halide ratio by blending four precursor solutions containing FA, FA + Cs, $PbBr_2$ and PbI_2. The combined flowrates remain pairwise constant according to $F_{\mathrm{FA}} + F_{\mathrm{FA+Cs}} = 2 \cdot \left(F_{\mathrm{PbBr_2}} + F_{\mathrm{PbI_2}}\right) = \text{constant}$, thus ensuring preservation of fixed concentrations of FA and Pb throughout.

To aid assessment of the error returned by the Kriging model, we evaluate the experimental error of our system. We do not expect a significant systematic error since the PL peak position of product particles shifts less than 4 nm over more than 180 minutes of continuous production (Figure S2). To assess reproducibility, we record spectra over the course of several hours, randomly switching experimental conditions within a set of five predetermined combinations of precursor flow rates (Figure 3b and c). For each set, we display deviations $\Delta\lambda_{\mathrm{max}}$ from the average PL peak maximum $\bar{\lambda}_{\mathrm{max}}$ ($\Delta\lambda_{\mathrm{max}} = \lambda_{\mathrm{max}} - \bar{\lambda}_{\mathrm{max}}$) over time (Figure 3d). The errors are homogenously distributed throughout parameter space with a standard deviation of ± 4 nm, including errors introduced by the limited accuracy of syringe pumps and temperature controller, spectrometer resolution as well as degradation of the precursor solutions over extended periods of time.

We first focus our attention on the synthesis of (Cs/FA)Pb(Br/I)$_3$ with controlled emission. Synthesis of formamidinium-based perovskite NCs requires an excess of FA over Pb, which we hold constant at $[\mathrm{FA}]/[\mathrm{Pb}] = 8$.[28] Reactions are performed at 120 °C to ensure the formation of nearly-monodisperse cubic nanocrystals (Figure S3). Compositional tuning is achieved by varying the Cs concentration and halide ratio, forming a two-dimensional parameter space. The parameter $x_{\mathrm{Cs}} = \frac{F_{\mathrm{FA}}}{F_{\mathrm{FA}}+F_{\mathrm{FA+Cs}}}$ parametrizes Cs doping, with values ranging from 0 for $[\mathrm{Cs}]/[\mathrm{Pb}] = 0$ to 1 for $[\mathrm{Cs}]/[\mathrm{Pb}] = 1.6$. In addition, x_{I} corresponds to the iodide ratio defined as $x_{\mathrm{I}} = \frac{[\mathrm{I}]}{[\mathrm{I}]+[\mathrm{Br}]} = \frac{F_{\mathrm{PbBr_2}}}{F_{\mathrm{PbBr_2}}+F_{\mathrm{PbI_2}}}$. It should also be noted that concentrations are related to the precursor solutions and generally do not correspond directly to crystal composition.[27] In a multi-dimensional parameter space, there may exist an infinite number of combinations yielding a specific PL peak wavelength, and thus we avoid the stalling of the algorithm search by adding an extra constraint that forces the

algorithm to select unvisited positions for a subsequent measurement. Initial measurement points lie on a homogeneous 4-by-4 grid distributed over the entire parameter space, which is discretized as a 40-by-40 grid corresponding to a resolution of about 0.5 µL/min with respect to precursor flow rates.

To illustrate our method, we identify reaction conditions that produce (Cs/FA)Pb(I/Br)$_3$ nanocrystals with target wavelengths of 560, 620 and 680 nm (Figure 4a). Starting from a set of initial measurements (grey points), MARIA iteratively selects subsequent measurement conditions that have the highest likelihood of reaching a target wavelength (colored points). Figure 4b illustrates the evolution of the statistical indicators Q_1 and Q_2 (defined above) for an increasing number of iterations. Sets of points obtained through MARIA with increasing lengths are randomly selected to assess the quality of the model independently of the sampling sequence. At first, with very few points, residuals exhibit negative bias ($Q_1 < 0$) with a variance larger than predicted by the model ($Q_2 > 1$), indicating a highly sensitive response surface that is likely not representative of the experimental system. The addition of more points in the region of interest produces a more reliable model with cross-validated residuals in good agreement with the Kriging model predictions ($Q_1 \to 0$, $Q_2 \to 1$). In this example, approximately 20 iterations are required to generate a robust response surface, corresponding to 36 measurements (including initial samples). Importantly, systematic screening cannot reach a comparable model robustness in the region of interest with so few measurements (Figure 5 and Figure S4). MARIA focuses on a region of interest to achieve a specific goal and perform experiments exclusively in the proximity of a target output. That said, systematic screening would provide a better overview of the entire parameter space than a target-oriented approach, and would thus be desirable if the goal was to investigate the general functional dependence of optical properties on reaction conditions.[52]

We evaluate the accuracy of the final model returned by MARIA by performing measurements at the conditions predicted to result in a PL peak of 680 nm. We define a spatially-weighted and normalized parameter ξ that follows the predicted line and increases according to $\mathrm{d}\xi = \sqrt{\mathrm{d}x_{\mathrm{Cs}}^2 + \mathrm{d}x_{\mathrm{I}}^2}$, starting from $\xi = 0$ at $x_{\mathrm{Cs}} = 0$ to $\xi = 1$ at $x_{\mathrm{Cs}} = 1$ (Figure 6a). Forty measurements are performed for increasing values of ξ and compared with the Kriging predictions (Figure 6b and c). A q-q plot of the residuals against normal quantiles confirms the excellent predictive ability of the final model (Figure 6d). Significantly, this implies that the model error is intrinsically comprised of the error linked to the interpolation and sampling (as determined in Figure 3d) without *a priori* inputs from the user. The model also serves as a platform to compare NCs with similar PL emission, as it is able to predict other spectral properties, such as FWHM (Figure 6e) and maximum intensity (Figure 6f). Indeed, we find that low- and mid-levels of Cs doping are detrimental to PL intensities and produce broader emission

peaks, possibly due to the higher Br content required to compensate the blue shift caused by caesium and reach the targeted emission peak wavelength of 680 nm.[28] Conversely, high Cs concentrations produce NCs exhibiting higher intensities and narrower emission peaks.

In light of the superior optical performance of multinary LHP systems detailed in the introduction, we extend the procedure to a three-dimensional chemical system for the synthesis of (Cs/Rb/FA)Pb(Br/I)$_3$ NCs with a target PL peak at 600 nm. We include an extra parameter x_{Rb}, directly proportional to the Rb doping concentration, increasing from $x_{\mathrm{Rb}} = 0$ at $[\mathrm{Rb}] = 0$ to $x_{\mathrm{Rb}} = 1$ at $[\mathrm{Rb}]/[\mathrm{Pb}] = 1.6$. Figure 7a displays the data with the 600 nm surface obtained by MARIA in a three-dimensional parameter space formed by x_{I}, x_{Cs} and x_{Rb}. Starting from 40 initial measurements spread on a truncated 4-by-4-by-4 grid (blue spheres), MARIA performs 60 measurements (red spheres) to generate an insensitive and reliable model (Figure S5). The entire procedure takes approximately three hours to complete and uses less than 50 mL of precursors solutions (< 75 mg of lead). Figure 7b and c show the values of FWHM and maximum intensity on the 600 nm iso-surface. With its small ionic radius, Rb^+ is not easily incorporated into the perovskite lattice, resulting in a small influence on PL peak wavelength and broadening.[71] However, it has been shown to have a significant impact on stability, forming a photoinactive phase that acts as a protective layer.[72] We also note that doping with Cs^+ is essential to ensure high PL intensities and reportedly increases phase stability of FA-based LHPs.[69] Based on these considerations and the model outputs, we are able to select several promising reaction conditions for further investigation in the form of QY measurements or studies on long-term photostability. In the current study, we would for example focus our attention on various points along the diagonal (*i.e.* $[\mathrm{Rb}] + [\mathrm{Cs}] = 1.6\,[\mathrm{Pb}]$ up to $[\mathrm{Rb}] \leq 1.2\,[\mathrm{Pb}]$ with halide ratios predicted by the 600 nm iso-surface) which exhibit narrower PL peaks and higher intensities when compared to the undoped NC composition.

Conclusions

We have successfully developed a high-throughput microfluidic platform for the rapid and automated identification of reagent concentrations that yield NCs with defined emission properties. An adaptive sampling algorithm based on a Kriging regression model computes a response surface based on spectroscopic measurements at previously visited experimental conditions and selects subsequent optimal sampling points with the highest likelihood of reaching a target PL peak wavelength. Importantly, the novel goal-seeking approach developed herein is straightforward compared to methods based on objective functions and is, in addition, computationally undemanding. The application of MARIA to the synthesis of (Cs/FA)Pb(Br/I)$_3$ and (Rb/Cs/FA)Pb(Br/I)$_3$ NCs with various target emission wavelengths results in models that efficiently capture the

experimental error and exhibit high accuracy after only a few dozen iterations. Moreover, the models also enable prediction of other observable spectral properties at the conditions of interest, thus providing a convenient basis for the selection of promising conditions to scale-up or for application-oriented performance and stability tests, in particular concerning stability, which remains a key challenge for the successful implementation of LHP materials in display applications. Stability tests represent a time-consuming task and should be performed on a minimal number of carefully selected material candidates.

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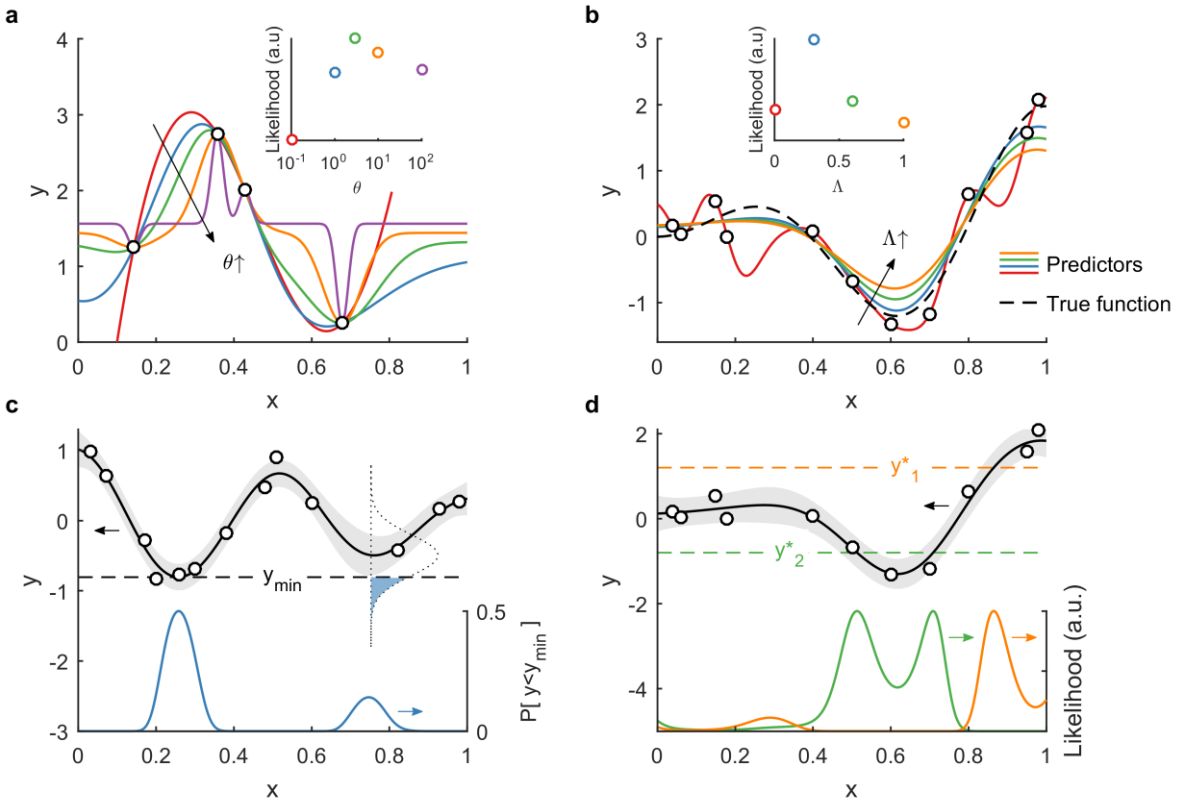

Figure 1. (a) Influence of θ on Kriging predictors applied to a set of four arbitrary data points with values 10^{-1}, 1, 3, 10 and 100. The inset shows the calculated likelihood for each predictor. MARIA automatically choses the predictor corresponding to the maximal likelihood. (b) Influence of the regression parameter, Λ, on Kriging predictors. Data points are generated by adding noise to an arbitrary function (dashed line). Starting from $\Lambda = 0$ (pure interpolation) larger values of Λ imply larger sampling errors. The inset shows the calculated likelihood of the predictors for increasing Λ. (c) Optimization approach: probability, *P*, to improve current predicted minimum $y_{\min}$ (blue curve). The probability is calculated by integrating the probability density function (dotted curve, shown for $x = 0.75$) with the mean given by the predictor (solid line) and variance (grey area) returned by Kriging. (d) Goal-seeking approach implemented by MARIA: likelihoods of the predictions to reach two different target values y_1^* and y_2^*. This one-step method calculates the likelihood directly from the Kriging parameters θ and Λ, without necessarily evaluating the predictor.

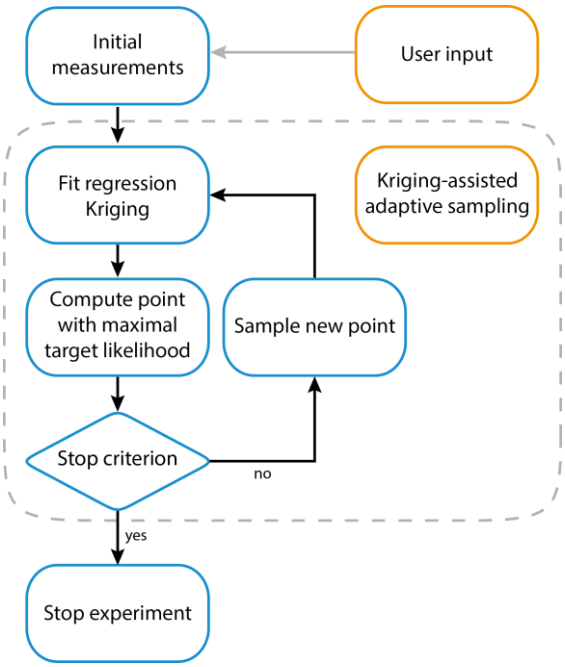

Figure 2. Flowchart describing the Kriging-based adaptive sampling procedure (MARIA). The process is fully automated, and user influence limited to the choice of a set of initial sampling points.

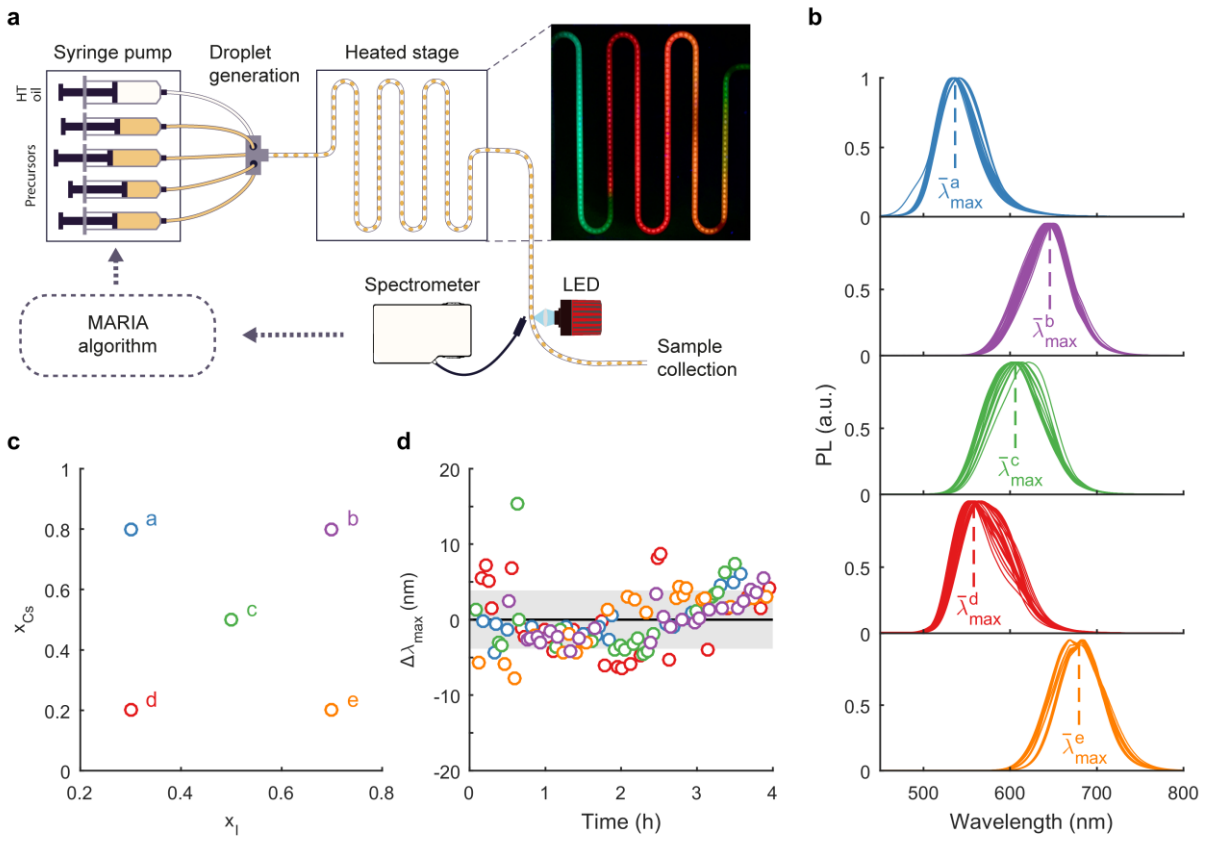

Figure 3. (a) Schematic of the experimental setup for the synthesis of (Cs/FA)Pb(Br/I)$_3$ NCs. The adaptive sampling algorithm iteratively adjusts the experimental conditions to drive the product nanocrystals toward a target emission wavelength based on spectroscopic measurements recorded thus far. The photograph shows stream of droplets containing the reaction mixture under UV exposure and after a change in halide ratio. (b) Experimental error is evaluated by randomly performing experiments at one of five selected reaction conditions (a, b, c, d and e) with Cs doping and halide ratio defined in (c). The mean emission peak wavelength $\bar{\lambda}^i_{\max}$ is calculated from the spectra at each experimental condition and used to compute $\Delta\lambda_{\max} = \lambda^i_{\max} - \bar{\lambda}^i_{\max}$. (d) The standard deviation of $\Delta\lambda_{\max}$ (grey area) corresponds to the experimental error of our system, limiting the accuracy of synthesized nanomaterials PL peak wavelength to ± 4 nm.

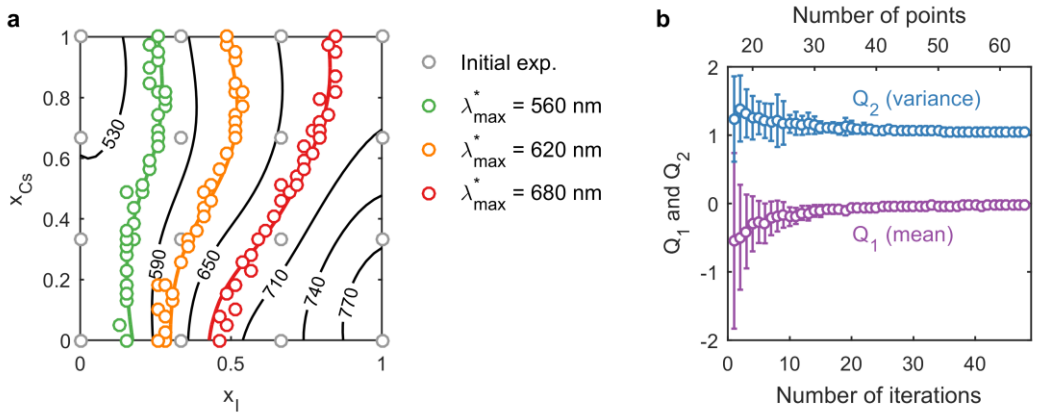

Figure 4. (a) A two-dimensional adaptive sampling experiment for the synthesis of (Cs/FA)Pb(Br/I)$_3$ NCs with targeted emission wavelengths, λ^*_{max}, of 560 nm, 620 nm and 680 nm. Starting from a set of initial measurements (grey points), reaction conditions are iteratively selected by varying Cs doping (x_{Cs}) and halide ratio (x_{I}) based on a Kriging model (solid contour lines). (b) First and second moments (Q_1 and Q_2) of standardized residuals obtained by "leave-one-out" cross-validation. Sets of measurements with increasing length are randomly selected 30 times in a row to yield a distribution independent of the sampling sequence. A robust model, *i.e.* when Q_1 and Q_2 consistently take values of 0 and 1, respectively, is reached after approximately twenty iterations.

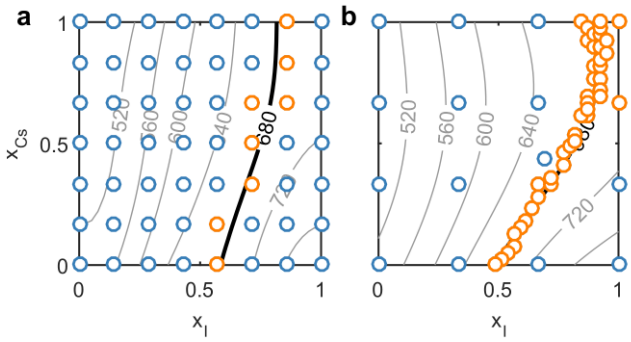

Figure 5. Systematic screening (a) compared to the MARIA procedure (b) after the same number of measurements (56 points) for a target PL peak wavelength of 680 nm. Orange data points are measurements where the PL emission is within our region of interest, *i.e.* 660–700 nm. Standardized cross-validated residuals of these points are characterized by $Q_1 = -0.17$ and $Q_2 = 1.8$ for (a) and $Q_1 = 0.06$ and $Q_2 = 1.0$ for (b). (see Figure S4 for the corresponding q-q plots) Even though the contour lines of the two resulting models exhibit similarities, the model obtained with MARIA is less sensitive and more representative of the experimental results.

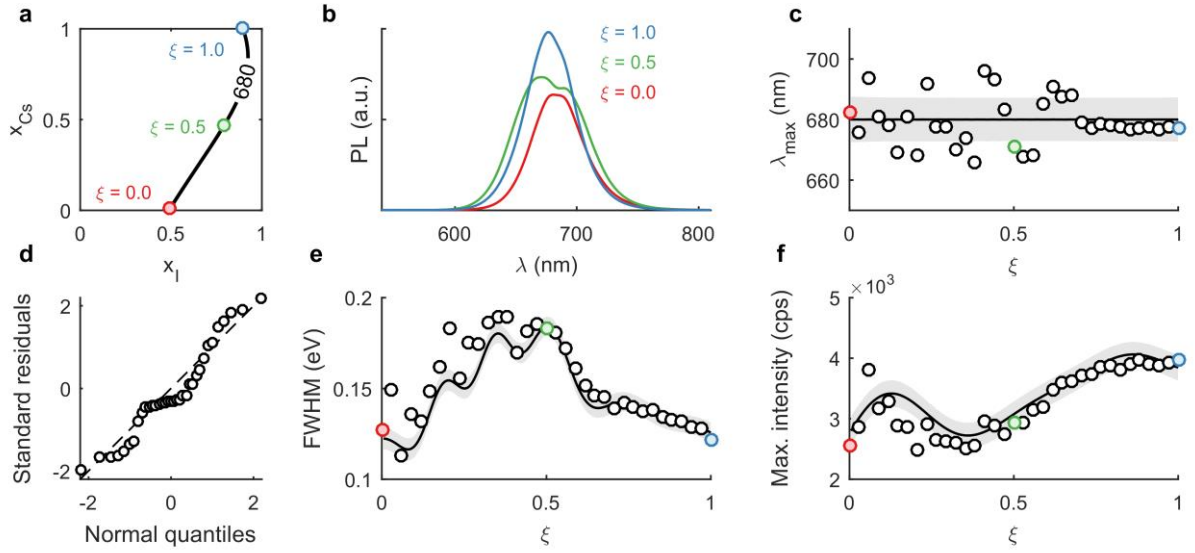

Figure 6. Validation of the model returned by MARIA for a targeted emission peak wavelength of 680 nm. (a) A spatial coordinate, ξ, is defined along the line of interest. (b) Experiments are systematically performed at the reaction conditions predicted by the model and the corresponding spectra are recorded. (c) Measured PL peak wavelengths, $\lambda_{\max}$, are compared to the model predictor (solid line) and its associated error (grey area). (d) Standardized residuals are computed and represented in a q-q plot against normal quantiles. The model is used to predict other spectral properties such as FWHM (e) and maximum intensity (f) at the conditions with predicted emission at 680 nm.

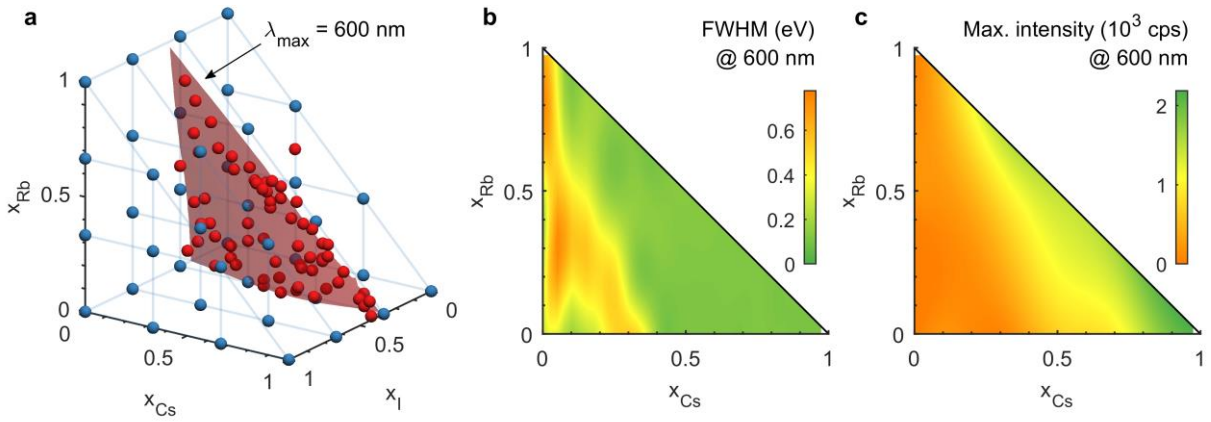

Figure 7. Adaptive sampling experiment for the synthesis of (Rb/Cs/FA)Pb(Br/I)$_3$ NCs in a three-dimensional parametric space with varying Cs doping (x_{Cs}), Rb doping (x_{Rb}) and halide ratio (x_{I}) and for a targeted emission wavelength of 600 nm. (a) Starting from a set of 40 initial measurements (blue spheres), MARIA selects conditions (red spheres) along the predicted 600 nm iso-surface (transparent red surface). FWHM (b) and maximum intensity (c) of NCs are predicted at the reaction conditions predicted by the iso-surface (projections on the x_{Cs}–x_{Rb} plane are represented for clarity).

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