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# AN AUTOMATIC MODEL-BUILDING ALGORITHM FOR SPARSE APPROXIMATION OF ROOM IMPULSE RESPONSES WITH ORTHONORMAL BASIS FUNCTIONS

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## ABSTRACT

Orthonormal Basis Function (OBF) models are used to define stable fixed-poles infinite impulse response filter structures that allow to incorporate knowledge about the resonant characteristics of a stable, causal and linear system. In the approximation of a room impulse response, OBF models can include knowledge about the room resonances as a set of poles, which appear nonlinearly in the structure. A novel algorithm is proposed, that avoids this nonlinear problem by iteratively estimating the poles and building the model. Some of the properties of OBF models, such as orthogonality and linearity-in-the-parameters, are exploited and the final model has the favorable property of being scalable. The OBF model provides a longer response than the all-zero model and is particularly suited in approximating the early response and the predominant resonances for relatively small model orders.

***Index Terms***— Orthonormal Basis Functions, Sparse approximation, Room Acoustics, Orthogonal Matching Pursuit

## 1. INTRODUCTION

Modeling of room acoustics refers to the description of the sound field inside a room. Non-parametric models are based on an approximation of the wave equation or on the geometrical properties of sound propagation. Parametric models, instead, approximate the room transfer function (RTF), which corresponds to the Green's function for given positions of the source and the receiver, by a rational function in the $z$-transform domain, under the assumption that the room is a stable, causal and linear system. This rational function can be parameterized in terms of zeros and poles by computing the roots of the numerator and denominator polynomials, respectively. The zeros represent anti-resonances in the system and time delays, while the poles represent the resonant modes of the room and the damping constants that appear in the Green's function [1].

The most common parametric model is the all-zero model, which corresponds to a truncation of the room impulse response (RIR) and is able to achieve an arbitrary degree of accuracy by using a high-order finite impulse response (FIR) filter, the order corresponding to the sample index at which the RIR is truncated. The number of parameters of the filter often has to be quite large in order to identify the inherent resonant properties of the system. Also, the actual parameter values depend strongly on the source and receiver position.

The number of parameters needed for approximating the RIR can be reduced by using all-pole and pole-zero models, which correspond to infinite impulse response (IIR) filters. All-pole models can describe room resonances by means of complex-conjugate pole pairs, but, since the poles have to be stable, only the minimum-phase characteristics of the RTF can be approximated and also true delays cannot be modeled. Given that the resonances are a property of the room, the parameter values of an all-pole model are less sensitive to changes in the source and receiver position. Pole-zero models can represent both resonances and time delays, as well as the minimum and non-minimum-phase components of the system. However, since the parameters appear nonlinearly in the model, no closed-form solution exists and nonlinear optimization techniques are required, possibly yielding instability or convergence to local minima.

An alternative to conventional parametric models is represented by models based on Orthonormal Basis Functions (OBFs) [2], which also correspond to an IIR filter but offer

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an asset in terms of stability, well-conditioning and flexibility. OBF models have a transversal structure with linear tap-coefficients (as in the all-zero model), thus allowing linear regression estimation. However, since the parameters related to the poles appear nonlinearly in the model structure, nonlinear optimization techniques are still required. An interesting method based on FIR-to-IIR conversion, similar to iterative algorithms for pole-zero models (e.g. the Stieglitz-McBride method [3]), has been proposed in [4] and applied to modeling of loudspeaker and room responses. In [5], we have proposed a method for approximating a target RIR, in which the nonlinear problem is avoided by selecting a set of poles from a grid defined over the unit disc, based on a sparse solution of an $\ell_1$-norm-penalized regression estimation problem, solved by means of convex optimization.

In this paper, a new algorithm is proposed, that estimates the poles and builds the model iteratively, also avoiding the nonlinear problem. Section 2 introduces the theoretical background of OBF models. Section 3 describes the algorithm which iteratively builds an OBF model by choosing the basis functions from a set of functions orthogonal to those previously selected, based on their correlation with the current residual signal. In Section 4, simulation results are shown, assessing the performance of the proposed algorithm in terms of approximation error. Section 5 concludes the paper.

## 2. ORTHONORMAL BASIS FUNCTION MODELS

OBF models define an IIR filter structure that embeds knowledge about resonant frequencies and damping constants. Since each basis function is defined by a pole, the first- and second-order dynamics of the system can be described by a set of real and complex poles, lying inside the unit circle to guarantee stability. To describe a resonance with bandwidth $B_1$ at frequency $f_1$ (both in Hz), a basis function $\Psi_1$ can be built using the pole $\xi_1 = \rho_1 e^{-j\vartheta_1}$, with angle $\vartheta_1 = 2\pi f_1/f_s$ and radius $\rho_1 = e^{-\pi B_1/f_s}$ (with $f_s$ the sampling frequency)[6][7]. The basis function is then given as

$$\Psi_1(q, \xi_1) = A_1 \frac{q^d}{q - \xi_1}, \tag{1}$$

with $q$ the forward shift operator, $d = \{0, 1\}$ a term defining simple or strict causality and $A_1 = \sqrt{1 - |\xi_1|^2}$ a normalization factor. A second resonance at $f_2$ can then be described by adding a second basis function using the pole $\xi_2 = \rho_2 e^{-j\vartheta_2}$, with angle $\vartheta_2 = 2\pi f_2/f_s$ and radius $\rho_2 = e^{-\pi B_2/f_s}$, given as

$$\Psi_2(q, [\xi_1, \xi_2]^T) = A_2 \frac{q^d(1 - \bar{\xi}_1 q)}{(q - \xi_1)(q - \xi_2)}, \tag{2}$$

with $A_2 = \sqrt{1 - |\xi_2|^2}$, where orthogonality between the two functions is provided by the zero in $q = 1/\bar{\xi}_1$ (the overline denotes complex conjugation). By applying this procedure repeatedly, multiple resonances can be modeled by using a

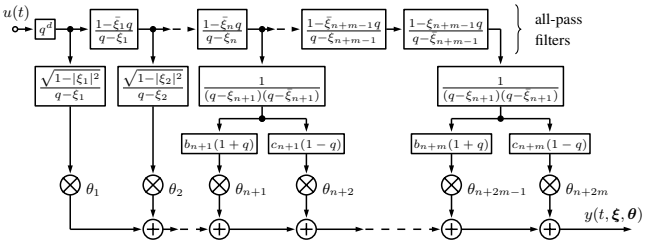


**Fig. 1**. The mixed-Kautz model structure, with parameters $b_i = |1 - \xi_i|\sqrt{1 - |\xi_i|^2/2}$ and $c_i = |1 + \xi_i|\sqrt{1 - |\xi_i|^2/2}$.

set of poles $\boldsymbol{\xi} = [\xi_1, \xi_2, \ldots, \xi_M]^T$, leading to the Takenaka-Malmquist model, with the $n^{\text{th}}$ basis function defined as

$$\Psi_n(q, \boldsymbol{\xi}) = q^d \left( \frac{\sqrt{1 - |\xi_n|^2}}{q - \xi_n} \right) \prod_{k=1}^{n-1} \left( \frac{1 - \bar{\xi}_k q}{q - \xi_k} \right), \tag{3}$$

in which orthogonality is obtained by a sequence of first-order all-pass filters defined by the poles $\xi_1, ..., \xi_{n-1}$.

A resonance at a non-zero frequency is modeled by a complex-conjugate pole pair, which, if inserted in the function in (3), generates a complex-valued response. Modifications of the model structure, as suggested in [8], allow to obtain a pair of real-valued responses for a complex pole $\xi_k$ and its complex-conjugate $\bar{\xi}_k$. Among OBF models allowing real-valued responses for the basis functions, a combination of the Takenaka-Malmquist model for real poles and the Kautz model [9] for complex poles will be used in this paper. This model structure, henceforth called mixed-Kautz model, has been used also in [4] and [5] and is depicted in Fig. 1 for $n$ real poles and $m$ pairs of complex-conjugate poles.

OBF models have some desirable properties which motivate our interest in adopting these models for approximating a target RIR. First, poles can be allocated anywhere inside the unit circle without problems of ill-conditioning, which afflict conventional pole-zero models, especially at high orders. This means that an arbitrary number of poles can be included in the model, making it suitable for the approximation of a RIR, which is often characterized by a large number of resonances. Second, the flexibility of OBF models lies in the possibility of distributing the poles unevenly in the frequency range, so that a larger number of poles may be concentrated in a specific frequency region where a higher accuracy is required. Third, the orthogonality of the basis functions provides a good bias/variance trade-off, enabling an approximation of the system with a favorable balance between accuracy and complexity. Additional advantages are the scalability, as will be shown in Section 3, and the fact that the same magnitude and phase responses for the output are obtained regardless of the ordering of the poles in the sequence of basis functions. Another consequence of orthogonality is that OBFs form a complete set in the Hardy space on the unit disc $\mathcal{H}_2(\mathbb{T})$, under the assumption that $\sum_{k=0}^{\infty}(1 - |\xi_k|) = \infty$ [8], such that any quadratically summable function can be approx-

imated with arbitrary accuracy by a linear combination of a certain finite number of basis functions.

A fourth important property is the linearity in the tap-coefficients, which can then be estimated in closed form by linear regression. Given an input signal $u(t)$, the output of an OBF model is given by (see Fig. 1, where $M = n + 2m$)

$$y(t, \boldsymbol{\xi}, \boldsymbol{\theta}) = \sum_{i=1}^{M} \theta_i \Psi_i(q, \boldsymbol{\xi}) u(t) = \sum_{i=1}^{M} \theta_i \varphi_i(t, \boldsymbol{\xi}), \quad (4)$$

where $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_M]$ are the tap-coefficients, and $\varphi_i(t, \boldsymbol{\xi})$ corresponds to the input signal $u(t)$ filtered by $\Psi_i(q, \boldsymbol{\xi})$. Since the $M$ columns $\boldsymbol{\varphi}_i(\boldsymbol{\xi}) = \{\varphi_i(t, \boldsymbol{\xi})\}_{t=1}^{N}$ of the matrix $\boldsymbol{\Phi}(\boldsymbol{\xi})$ are orthogonal to each other, the least-squares (LS) estimate for the tap-coefficients $\boldsymbol{\theta}$, given a data set $\{\boldsymbol{u}, \boldsymbol{y}\} = \{u(t), y(t)\}_{t=1}^{N}$ of size $N$, with $\boldsymbol{u}$ a unit impulse signal vector, reduces to $\hat{\boldsymbol{\theta}}_N^{\mathrm{LS}} = \boldsymbol{\Phi}^T \boldsymbol{y}$.

## 3. AUTOMATIC MODEL-BUILDING ALGORITHM

Sparse approximation aims at compactly representing a signal by a linear combination of a subset of elements (called predictors or atoms) from an overcomplete basis (sometimes called dictionary). Many approaches have been suggested [10], one of them being the minimization of functionals, i.e. the $\ell_1$ norm in the Least Absolute Shrinkage and Selection Operator (LASSO) [11]. An alternative is to use a greedy algorithm for iteratively selecting those elements of the basis that best represent the signal. For a fixed orthonormal basis, the sparse approximation problem reduces to finding the $M$ elements that have the largest regression coefficients [12].

In [5], a sparse solution for the pole estimation problem in an OBF model has been obtained, by solving the LASSO using convex optimization. However, the estimation step was performed on a large non-orthogonal basis not generated from the mixed-Kautz model, in which the selected poles were thus used only in a second step. Here, we introduce a new algorithm that jointly estimates the poles and builds the mixed-Kautz model, by adding functions to the orthogonal basis in an iterative fashion. The algorithm resembles the well-known Orthogonal Matching Pursuit (OMP) [13], an iterative greedy algorithm that selects the predictors which are most correlated with the current residual part of the signal, which is then projected onto the space defined by the predictors already selected. The difference in the proposed algorithm, henceforth called OBF-MP, is that the set of all candidate predictors is not available and has to be computed at each iteration based on the predictors already added to the orthogonal basis.

The algorithm exploits some properties of OBF models such as orthogonality and linearity-in-the-parameters. The nonlinear problem of estimating the poles is bypassed, as in [5], by defining a set of $P$ candidate poles $\boldsymbol{\xi}_p = \{\xi_1, \ldots, \xi_P\}$ placed over the unit disc with an arbitrary distribution in terms of angle and radius. Then, at each iteration $k$, a matrix $\boldsymbol{\Phi}_k$ is built with candidate predictors $\boldsymbol{\varphi}_i$, which are the responses of the OBFs to the input vector $\boldsymbol{u}$, computed for each pole in $\boldsymbol{\xi}_p$ and orthogonal to the predictors in the current basis $\boldsymbol{\Phi}_{k-1}^{\mathcal{A}}$.

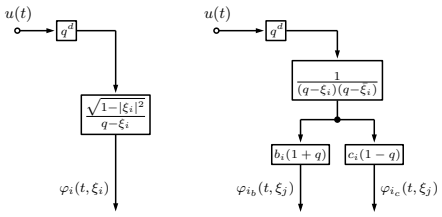


**Fig. 2**. Structures for generating the predictors of $\boldsymbol{\Phi}_1(\boldsymbol{\xi}_p)$. (left) For a real pole and (right) for a pair of complex-conjugate poles.

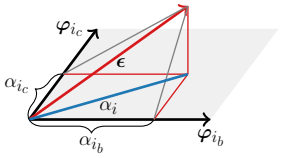


**Fig. 3**. Graphical interpretation of the correlation between the residual vector $\boldsymbol{\epsilon}$ and a pair of predictors generated by a complex pole $\xi_i$.

The set of active poles $\boldsymbol{\xi}_0^{\mathcal{A}}$ and the set of active predictors, i.e. the orthonormal basis, $\boldsymbol{\Phi}_0^{\mathcal{A}}$ are initially empty ($n_{\mathcal{A}} = 0$). Also the target approximation vector $\hat{\boldsymbol{y}}_0$ and the approximated residual vector $\hat{\boldsymbol{\epsilon}}_0$ are initialized to zero. The current residual signal is set to $\boldsymbol{\epsilon}_0 = \boldsymbol{y}$. The matrix $\boldsymbol{\Phi}_1(\boldsymbol{\xi}_p)$ of candidate predictors is built using the structures in Fig. 2. Notice that for each complex pole pole pair two real-valued responses are generated, as explained in Section 2.

At each iteration $k$, OBF-MP selects the predictor(s) in $\boldsymbol{\Phi}_k$ having maximum correlation with the residual vector $\boldsymbol{\epsilon}_k$. While for predictors generated by real poles the correlation $\alpha_i$ is given by the projection of $\boldsymbol{\epsilon}_k$ onto the predictor $\boldsymbol{\varphi}_i$ ($\alpha_i = \boldsymbol{\varphi}_i^T \boldsymbol{\epsilon}_k$), the correlation for a pair of predictors $\boldsymbol{\varphi}_{i_b}$ and $\boldsymbol{\varphi}_{i_c}$ of a complex-conjugate pole pair $\xi_i$ is the projection of $\boldsymbol{\epsilon}_k$ on the plane that they define (see Fig. 3), and is given by

$$\alpha_i = \sqrt{\alpha_{i_b}^2 + \alpha_{i_c}^2} = \sqrt{(\boldsymbol{\varphi}_{i_b}^T \boldsymbol{\epsilon}_k)^2 + (\boldsymbol{\varphi}_{i_c}^T \boldsymbol{\epsilon}_k)^2}. \quad (5)$$

The predictor(s) with maximum absolute correlation $\alpha_i$ is added to the basis $\boldsymbol{\Phi}_k^{\mathcal{A}}$ and the corresponding pole is included in the set of active poles $\boldsymbol{\xi}_k^{\mathcal{A}}$.

At each next iteration $k+1$, a new matrix $\boldsymbol{\Phi}_{k+1}$ of candidates is created by building predictors for all poles in $\boldsymbol{\xi}_p$, all orthogonal to the predictors already in the current basis $\boldsymbol{\Phi}_k^{\mathcal{A}}$, accordingly to the mixed-Kautz model structure. The residual signal $\boldsymbol{\epsilon}_{k+1}$ is then updated by subtracting from $\boldsymbol{\epsilon}_k$ the approximated residual vector, which is obtained in the previous iteration by $\hat{\boldsymbol{\epsilon}}_k = \boldsymbol{\varphi}_i \alpha_i$ (for a complex-conjugate pole pair $\hat{\boldsymbol{\epsilon}}_k = [\boldsymbol{\varphi}_{i_b}\, \boldsymbol{\varphi}_{i_c}][\alpha_{i_b}\, \alpha_{i_c}]^T$). In fact, since $\boldsymbol{\epsilon}_k$ is orthogonal to each basis function in the current basis $\boldsymbol{\Phi}_{k-1}^{\mathcal{A}}$, the approximated residual can be computed from the last added predictor(s) by using the maximum correlation $\alpha_i$ as regression coefficient. The target approximation $\hat{\boldsymbol{y}}_k$ is obtained by adding

the approximated residual $\hat{\boldsymbol{\epsilon}}_k$ at each iteration. It follows that the model built with OBF-MP is scalable, in the sense that a model of smaller order $M^-$ can be obtained starting from a model of order $M$ by selecting the first $M^-$ functions in the basis or a model of higher order $M^+$ can be computed by running extra iterations.

**Algorithm 1** OBF-MP algorithm

$\boldsymbol{\xi}_p = \{\xi_1, \ldots, \xi_P\}$ ▷ Define poles in the pole grid
$\boldsymbol{\Phi}_0^{\mathcal{A}} = \emptyset, n_{\mathcal{A}} = 0$ ▷ Initialize set of active predictors (basis)
$\boldsymbol{\xi}_0^{\mathcal{A}} = \emptyset$ ▷ Initialize the set of active poles
$\hat{\boldsymbol{y}}_0 = \mathbf{0},\ \hat{\boldsymbol{\epsilon}}_0 = 0,\ \boldsymbol{\epsilon}_0 = \boldsymbol{y}$ ▷ Initialize signal vectors
$k = 1$ ▷ $k$: iteration counter
**while** $n_{\mathcal{A}} < M$ **do** ▷ $M$: desired model order
  $\boldsymbol{\epsilon}_k = \boldsymbol{\epsilon}_{k-1} - \hat{\boldsymbol{\epsilon}}_{k-1}$ ▷ Update the current residual vector
  Build $\boldsymbol{\Phi}_k(\boldsymbol{\xi}_p)$ ▷ Build matrix of candidate predictors $\boldsymbol{\varphi}_i$
  $i = \arg\max_i |\alpha_i|$ ▷ Find $\boldsymbol{\varphi}_i$ max. correlated with $\boldsymbol{\epsilon}_k$
  $\boldsymbol{\xi}_k^{\mathcal{A}} = [\boldsymbol{\xi}_{k-1}^{\mathcal{A}}\ \xi_i]$ ▷ Add selected pole to active pole set
  **if** $\xi_i$ real **then** ▷ Update basis and approximated residual
    $\boldsymbol{\Phi}_k^{\mathcal{A}} = [\boldsymbol{\Phi}_{k-1}^{\mathcal{A}}\ \ \boldsymbol{\varphi}_i],\ n_{\mathcal{A}} = n_{\mathcal{A}} + 1$
    $\hat{\boldsymbol{\epsilon}}_k = \boldsymbol{\varphi}_i \alpha_i$
  **else if** $\xi_i$ complex **then**
    $\boldsymbol{\Phi}_k^{\mathcal{A}} = [\boldsymbol{\Phi}_{k-1}^{\mathcal{A}}\ \ \boldsymbol{\varphi}_{i_b}\ \ \boldsymbol{\varphi}_{i_c}],\ n_{\mathcal{A}} = n_{\mathcal{A}} + 2$
    $\hat{\boldsymbol{\epsilon}}_k = [\boldsymbol{\varphi}_{i_b}\ \boldsymbol{\varphi}_{i_c}][\alpha_{i_b}\ \alpha_{i_c}]^T$
  **end if**
  $\hat{\boldsymbol{y}}_k = \hat{\boldsymbol{y}}_{k-1} + \hat{\boldsymbol{\epsilon}}_k$ ▷ Update target approximation vector
  $k = k + 1$
**end while**

## 4. SIMULATION RESULTS

The OBF-MP algorithm has been tested on $R = 8$ data sets, each consisting of a unit impulse as the input signal $\boldsymbol{u}$ and one measured target RIR from the MARDY database [14], truncated to $N = 2000$ samples and with no delay, as the output signal $\boldsymbol{h}_r$, $r = 1, \ldots, R$. The grid used has $P = 3000$ poles, with 30 different radii from 0 to 0.99, and 100 different angles from 0 to $\pi$, both distributed logarithmically, so that more poles are concentrated at low frequencies and closer to the unit circle.

An approximation $\hat{\boldsymbol{h}}_r$ with different model orders $M$ has been computed for each target RIR $\boldsymbol{h}_r$ using the OBF-MP algorithm, the all-zero model, and the warped BU method [15] suggested in [4] (with Bark-warping factor $w = 0.766$). The measure used is the normalized mean-square error (NMSE) both in the time and frequency domain, averaged over all $R$ RIRs. The error in the time domain, given by

$$h_{\text{NMSE}} = 10 \log_{10} \frac{1}{R} \sum_{r=1}^{R} \frac{\|\boldsymbol{h}_r - \hat{\boldsymbol{h}}_r\|_2^2}{\|\boldsymbol{h}_r\|_2^2}, \tag{6}$$

has been computed on the complete impulse response, on the early response of length $M$ samples and on the late response of length $N - M$. Results show that OBF-MP produces a smaller approximation error in the early response than the BU method, with a big improvement for relatively small orders (50-100), while in the late response performances are comparable (left column of Fig. 4).

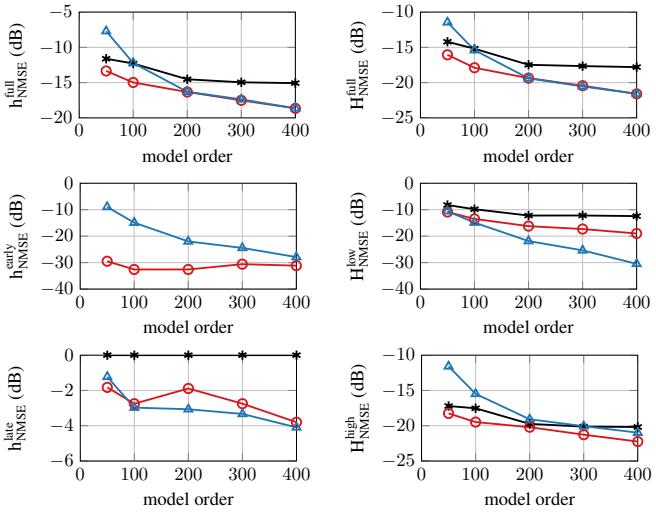


**Fig. 4**. (left) The average NMSE in (6) for the entire response (top) and for the early (middle) and late response (bottom). (right) The average NMSE in (7) for the entire spectrum (top) and for the frequency regions $[0, \frac{\pi}{6}]$ (middle) and $[\frac{\pi}{6}, \pi]$ (bottom). All-zero model (—✱—), OBF-BU model (—△—), and OBF-MP model (—○—).

The frequency domain error, given by

$$H_{\text{NMSE}} = 10 \log_{10} \frac{1}{R} \sum_{r=1}^{R} \frac{\|\boldsymbol{H}_r - \hat{\boldsymbol{H}}_r\|_2^2}{\|\boldsymbol{H}_r\|_2^2}, \tag{7}$$

has been computed on the whole spectrum and in the frequency regions $[0, \frac{\pi}{6}]$ and $[\frac{\pi}{6}, \pi]$. Results show that OBF-MP outperforms the all-zero model in general. Again, the algorithm gives the best improvement for relatively small orders, where it performs similarly to the BU method in the lower part of the spectrum, but is better able to approximate the spectral envelope in the high-frequency region (right column of Fig. 4). A comparison with our previous method in [5] is not included here, but OBF-MP appears to give better results, being also faster and scalable.

## 5. CONCLUSION

A novel algorithm, called OBF-MP, has been proposed for approximating a target RIR using an OBF model. The algorithm avoids the nonlinear problem of estimating the poles by constructing the model iteratively from a set of functions, built from a set of poles distributed over the unit disc. At each iteration, the algorithm selects the function that best approximates the residual part of the target RIR. Simulation results show that the OBF model built with the OBF-MP algorithm is particularly efficient for relatively small orders, providing a longer response and a better frequency resolution than the all-zero model, while approximating the early response better than the OBF model computed with the BU method in [4].

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