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# On Coded and Multi Dimensional Partial Response Signaling

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**Abstract**

Optimal finite partial response signals based on 2 and 4 PAM have been found by Said and Anderson [1]. The encoder is a simple discrete-time filter, whose combination of bandwidth and Euclidian distance is optimized. Here we extended the idea to the case where the modulated symbols are first encoded by a short convolutional encoder. This gives power gains of 1–3 dB while maintaining the same bandwidth. We also investigate possible gains from multi dimensional partial response signaling.

## 1. INTRODUCTION

The CPM, TCM and partial response signaling (PRS) classes of coded modulation are well known. In the last class are intersymbol interference removal and schemes based on filtering and real number discrete time convolution. These classes operate in different parts of the energy–bandwidth plane and PRS in particular is characterized by narrow bandwidth and high energy per bit.

Partial response signaling reduces the consumed bandwidth by introducing intentional ISI. Forney [2] showed that maximum–likelihood sequence estimation of sequences in presence of ISI can be accomplished with a matched filter and the Viterbi algorithm. When the ISI is severe reduced complexity algorithms [3] must be used.

Partial response signaling was first introduced by Lender [4]. Later, much research has gone in to finding optimal partial response pulses. Chan [5] and Foschini [6] have both attacked the problem of finding optimal pulses for linear PRS under bandwidth constraints. In both cases the ISI was limited to small duration. More recently Said [1] showed that finding a optimal PRS pulse is a linear programming problem (LPP). By using this approach he derived optimal pulses out to 15 taps. In this paper we have extended the work of Said. In [1] the data symbols presented to the PRS encoder were uncoded, here we find optimal pulses for coded data symbols. Furthermore a complex valued pulse can represent a two dimensional PRS scheme, and also this is a LPP. The gain of using two dimensions is roughly 1 dB. By proceeding to higher dimesionality than two further gains could be possible. However finding a LP formualtion of multi dimensional PRS is still an open problem. Heuristic search directly over the taps could be employed, but this is a tough optimization problem when the number of taps is large [7]. Instead we derived an suboptimal formulation which is based on a LP. This will give us quick insight in the magnitudes of possible gains for multi dimensional PRS.

The paper is organized as follows: in section 2 we give an introduction to Optimal PRS (OPRS). In section 3 we give the results of Coded Optimal PRS (CO-PRS). In section 4 we extend OPRS to Multi dimensional PRS. We sum the paper up in section 5.

## 2. INTRPDUCTION TO OPRS

We synthesize PRS by discrete–time convolution followed by a modulator. The system model for OPRS are shown in figure 1. We now follow Said's deriva-

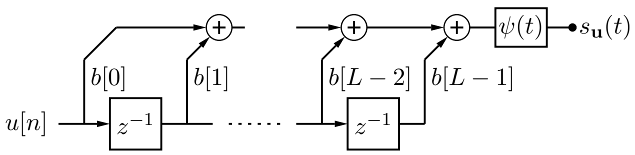


Figure 1: System model

tions to obtain the linear formulation of OPRS, this is necessary in order to later derive a suboptimal linear formulation for multi dimensional PRS.

The modulation signal transmitted over the channel is

$$s_{\mathbf{u}}(t) = \sum_{n=-\infty}^{\infty} u[n]h_c(t-nT) \tag{1}$$

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where $T$ is the symbol time and $h_c(t)$ is a spectrum shaping time-continuous pulse with unit energy. The sequence $u[n]$ consists of uncoded M-ary PAM symbols. The pulse $h_c(t)$ can in turn be represented as

$$h_c(t) = \sum_{n=0}^{L-1} b[n]\psi(t - nT) \tag{2}$$

where $\psi(t)$ is an orthogonal interpolation signal such as the root raised cosine pulse. To evalute bandwidth the *spectral concentration* (SPC) in the frequency interval $[-W, W]$ is used. This is defined as

$$C_h(W) = \frac{\int_{-W}^{W} |H_c(f)|^2 df}{\int_{-\infty}^{\infty} |H_c(f)|^2 df} = \int_{-W}^{W} |H_c(f)|^2 df \tag{3}$$

if $h_c(t)$ has unit energy. $W$ is the physical bandwidth. For $C_h(W)$ we use 99 % and 99.9 %. To compare different modulation schemes, we use the normalized bandwidth

$$\text{NBW} = \frac{WT}{R} \qquad \text{Hz-s/bit.} \tag{4}$$

If the data alphabet is suitable normalized [1] then the normalized Euclidian square distance between two signals $s_{\mathbf{a}}$ and $s_{\mathbf{b}}$ generated by the (causal) data sequences $\mathbf{a}$ and $\mathbf{b}$ is

$$\begin{aligned} d^2(\mathbf{a}, \mathbf{b}) &= \int_0^{\infty} |s_{\mathbf{a}}(t) - s_{\mathbf{b}}(t)|^2 dt \\ &= \int_{-\infty}^{\infty} \left| \sum_{n=0}^{\infty} (a[n] - b[n]) h(t - nT) \right|^2 dt \\ &= \int_{-\infty}^{\infty} \left| \sum_{n=0}^{\infty} \xi[n] h(t - nT) \right|^2 dt \\ &= \sum_{n=0}^{\infty} \sum_{m=0}^{\infty} \xi[n] g[m - n] \xi[m], \end{aligned} \tag{5}$$

where

$$g[m - n] = \int_{-\infty}^{\infty} h(t - nT) h(t - mT) dt. \tag{6}$$

It is now possible to simplify (5) to obtain the linear equation

$$d^2(\mathbf{a}, \mathbf{b}) = d^2(\xi) = \sum_{-\infty}^{\infty} g[n] r_{\xi}[n], \tag{7}$$

where $r_{\xi}[n]$ is the autocorrelation of $\xi$. In the same way it is possible to simplify (3) to a linear equation of $g[n]$. Furthermore there exists a set of linear equations on $g[n]$ that guarantees the existance of a pulse $h_c(t)$ having $g[n]$ as autocorrelation function.

Given a set of error events it is straightforward to set up a LP [1] to solve for the optimal pulse $h_c(t)$ of the form (2). To handle the fact that there exists an infinite number of error events Said derived the following iterative algorithm to solve for the optimal pulse [1]:

1. Initialize an error event set $\mathcal{E}$ with a few error events.
2. Find the optimal set of taps for $\mathcal{E}$, denote the solution $b^o$ (solve LP).
3. Find the actual $d^2_{\min}$ and the corresponding error event $\xi_{\min}$.
4. If $\xi_{\min} \in \mathcal{E}$ then stop: $b^o$ is optimal. Otherwise, add $\xi_{\min}$ to $\mathcal{E}$ and go to step 2.

The obtained results are very good, in the narrowband region the performance of OPRS improves on TCM.

## 3. CODED OPTIMAL PRS

Since the symbols presented to the linear filter for OPRS are uncoded, every possible error event is valid. Furthermore the minimum distance can never exceed the trivial upper bound $6 \cdot log_2 M/(M-1)$ where $M$ is the alphabet size. However, by first encoding the information symbols by a convolutional encoder and then optimize the taps using Said's algorithm it is possible to get a larger minimum distance while maintaining the same bandwidth. The system model is given in figure 2 where $R$ denotes the number of information bits per PAM symbol and $r$ denotes the number of coded bits among the $R$ input bits. Furthermore we denote the constraint length of the convolutional encoder by $\nu$.

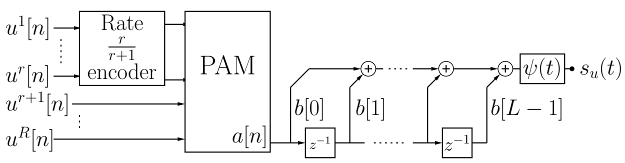


Figure 2: System model for Coded Optimal PRS.

In view of the LP, the convolutional code removes some of the constraints, so the minimum distance must increase, however the normalized bandwidth is increased so combined energy–bandwidth gains are not ensured by the convolutional code.

Searching for the optimal generator is done via exhaustive search. If the connection polynomials of the convolutional encoder are denoted by $\{g_{ij}\}$ and the least significant bit of the PAM mapper is indexed by 1 then the encoders satisfying $g_{11} = g_{1\nu} = 0$ and $g_{21} = g_{2\nu} = 1$ are always best. This is found by experience and is motivated by the fact that if this is true then it can be showed that every error event must start and end with the error symbols $\pm 4, \pm 6, \ldots$. We have observerd that this is crucial for producing a high Euclidian minimum distance.

The iterative algorithm described in section 2 needs only to be modified in step number 3; a new algorithm must be employed in order to account for the convolutional code.

The results are very good, COPRS most often improves on OPRS. A collection of obtained minimum distances are tabulated in appendix A. Most often The length of the linear filter can be decreased when applying the convlutional ecoder, however the alphabet size is increased.

Decoding is performed using the $M$-algorithm. The $M$ in the $M$-algorithm is slightly larger for COPRS than for OPRS. Furthermore the simulations reflects the gains in minimum distance well.

## 4. MULTI DIMENSIONAL PRS

Multi dimensional PRS is nothing new, Xia [7] have done much work in this field and uses the iterative algorithm that Said invented. However no method how to find the optimal pulses are given. Here we present a method of finding a suboptimal coded modulation scheme using linear programming.

Two dimensional PRS are represented as an complex valued pulse $h(t)$, here we proceed to 4 dimensions but the extension to any dimensionality is obvious. In a four dimensional PRS system we assume two independent complex valued input data streams, $\mathbf{u[n]} = (u_1[n], u_2[n])$, and a set of complex valued pulses $\{h_{ij}, i \leq 2, j \leq 2\}$. Two independent bandpass channels are used for transmitting the data signals which are formed as

$$s^i_{\mathbf{u}}(t) = \sum_{j=1}^{2} \sum_{n=-\infty}^{\infty} u_j[n] h_{ij}(t - nT), i = 1, 2 \qquad (8)$$

This is illustrated in figure 3

Given two sequences of data vectors, $\mathbf{u}^{'}[\mathbf{n}] = (u^{'}_1[n], u^{'}_2[n])$ and $\mathbf{u}^{''}[\mathbf{n}] = (u^{''}_1[n], u^{''}_2[n])$, and defining $e_i[n] = u^{'}_i[n] - u^{''}_i[n]$ the Euclidian distance between the 4 dimensional PRS signals generated by that data is

$$\begin{aligned} d^2(\mathbf{e}) &= \sum_{k=1}^{2} \int_{-\infty}^{\infty} |s^k_{\mathbf{u}'}(t) - s^k_{\mathbf{u}''}(t)|^2 dt \\ &= \sum_{k=1}^{2} \int_{-\infty}^{\infty} |s^k_{\mathbf{e}}(t)|^2 dt \\ &= \cdots \\ &= \sum_{n=-\infty}^{\infty} \sum_{i=1}^{2} \sum_{j=1}^{2} g_{ij}[n] r^*_{ij}[n], \end{aligned} \qquad (9)$$

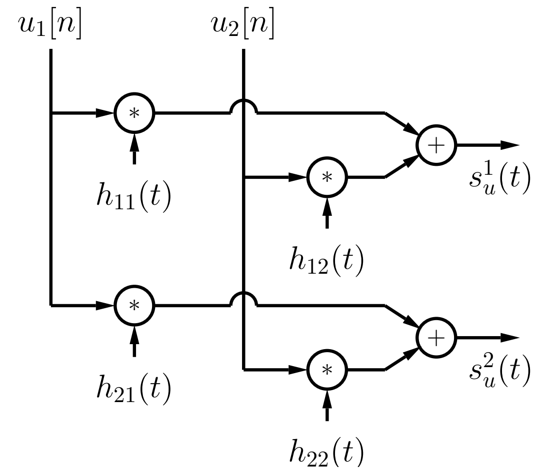


Figure 3: System model for 4–dimensional PRS.

where

$$g_{ij}[n] = \sum_{k=1}^{2} \int_{-\infty}^{\infty} h_{ki}(t + nT) h^*_{kj}(t) dt, \qquad (10)$$

and

$$r_{ij}[n] = \sum_{m=-\infty}^{\infty} e^*_i[m] e_j[n + m]. \qquad (11)$$

This means that the Euclidian distance of 4 dimensional PRS can be calculated from linear equations with $g_{ij}$ as variables.

We will do some simplifications to figure 3 in order to get easier expressions. We set

$$\begin{aligned} h_{22}(t) &= h_{11}(t) \\ h_{21}(t) &= h_{12}(t). \end{aligned} \qquad (12)$$

This gives exactly the same properties for $s^2_{\mathbf{u}}$ as for $s^1_{\mathbf{u}}$ and therefore we denote signals in the sequal just by $s_{\mathbf{u}}$.

Since $u_1[n]$ and $u_2[n]$ are independent the power spectral density of $s_{\mathbf{u}}(t)$ equals

$$\frac{\sigma^2_u}{T} \left( |H_{11}(f)|^2 + |H_{12}(f)|^2 \right) \qquad (13)$$

where $\sigma^2_u$ denotes $\mathcal{E}\{u^2_k[n]\}$. The average energy per data symbol in one channel, $E_s$, equals

$$E_s = \sigma^2_u(\lambda_{11}(0) + \lambda_{12}(0)) \qquad (14)$$

where $\lambda_{ij}(t)$ is the autocorrelation function of $h_{ij}(t)$.

The average energy per data bit is

$$E_b = \frac{E_s + E_s}{\log_2 M_c^2} = \frac{2E_s}{\log_2 M_c^2} = \frac{\sigma_u^2}{\log_2 M_c} \quad (15)$$

if

$$\lambda_{11}(0) + \lambda_{12}(0) = 1. \quad (16)$$

To measure bandwidth of the modulated signals we use the spectral concentration.

$$SPC(W) = \int_{f_s-W}^{f_s+W} |H_{11}(f)|^2 + |H_{12}(f)|^2 df \quad (17)$$

Since the filter is complex valued it does not have to be centered at 0 so the integration runs between $f_s - W$ and $f_s - W$ where $f_s$ is a frequency offset. The filters $h_{ij}(t)$ is built up as interpolated FIR filters

$$h_{ij}(t) = \sum_{k=0}^{L-1} b_{ij}[k]\psi(t - kT) \quad (18)$$

where $L$ is the length of the FIR filter $b_{ij}[n]$ and $\psi(t)$ is a interpolation pulse, such as a root raised cosine.

If we are using $g_{ij}[n]$ as variables in a LP we must find admissibility constraints when we can find causal FIR filters from $g_{ij}[n]$. This is an unsolved problem for dimensionality above 2. By restricting the problem to a special kind of pulses the problem can be avoided. On the other hand the obtained results are not longer optimal. Our restrictions are the following

1. $b_{11}[n]$ is chosen arbitrary.
2. $b_{12}[n] = b_{11}[n] * c[n]$, where $c[n]$ is known FIR filter of length $M + 1$.

Some more notation: we denote $b_{11}[n]$ just by $b[n]$ and $g_b[n]$ is the sampled autocorrelation of $b[n]$. Since we are dealing with only one unknown filter there is no problem with admissibility. We can use Said's original constraint

$$\sum_{k=-\infty}^{\infty} g_b[k]e^{-j2\pi kf} \geq 0, \text{ for all } f \in (-1/2, 1/2]. \quad (19)$$

It is now straight forward to calculate $g_{ij}[n]$,

$$\begin{aligned} g_{11}[n] &= \dots \\ &= g_b[n] * v[n] + g_b[n] * g_c[n] * v[n] \\ &= g_{22}[n]. \end{aligned} \quad (20)$$

where

$$v[n] = \int_{-\infty}^{\infty} \psi(t + nT)\psi^*(t)dt, \quad (21)$$

and $g_c[n]$ is the autocorrelation of $c[n]$. Furthermore it turns out that

$$\begin{aligned} g_{12}[n] &= \dots \\ &= g_b[n] * c^*[-n] * v[n] + g_b[n] * c[n] * v[n] \\ &= g_{21}[n]. \end{aligned} \quad (22)$$

Combining this with (9) gives

$$d^2(\mathbf{e}) = \sum_{n=-\infty}^{\infty} g_b[n] \sum_{i=1}^{2}\sum_{j=1}^{2} \mu_{ij}^*[n], \quad (23)$$

where

$$\begin{aligned} \mu_{11}[n] &= r_{11}[n] * v[n] + r_{11}[n] * v[n] * g_c[n] \\ \mu_{22}[n] &= r_{22}[n] * v[n] + r_{22}[n] * v[n] * g_c[n] \\ \mu_{12}[n] &= r_{12}[n] * c^*[-n] * v[n] + r_{12}[n] * c[n] * v[n] \\ \mu_{21}[n] &= r_{21}[n] * c^*[-n] * v[n] + r_{21}[n] * c[n] * v[n]. \end{aligned} \quad (24)$$

Turning to bandwidth, evaluating the first term of the r.h.s of (17) gives

$$\begin{aligned} &\int_{f_s-W}^{f_s+W} |H_{11}(f)|^2 df = \\ &= \sum_{k=1-L}^{L-1} g_b[n] \int_{f_s-W}^{f_s+W} |\Psi(f)|^2 e^{-j2\pi nfT} df = \\ &= \sum_{k=1-L}^{L-1} g_b[n]\chi^*[n] \end{aligned} \quad (25)$$

which is just Said's original spectral concentration. The second term is somewhat more challenging:

$$\begin{aligned} H_{12}(f) &= \Psi(f) \sum_{n=0}^{L+M-1} (b * c)[n]e^{-j2\pi nfT} \\ &= \dots \\ &= \Psi(f)C(f) \sum_{k=0}^{L-1} b[k]e^{-j2\pi kfT}, \end{aligned} \quad (26)$$

therefore

$$|H_{12}(f)|^2 = |\Psi(f)|^2|C(f)|^2 \sum_{k=1-L}^{L-1} g_b[n]e^{-j2\pi nfT}. \quad (27)$$

So

$$\begin{aligned} &\int_{f_s-W}^{f_s+W} |H_{12}(f)|^2 df = \\ &= \sum_{k=1-L}^{L-1} g_b[n] \int_{f_s-W}^{f_s+W} |\Psi(f)|^2|C(f)|^2 e^{-j2\pi nfT} df = \\ &= \sum_{k=1-L}^{L-1} g_b[n]\beta^*[n]. \end{aligned} \quad (28)$$

Now (17) becomes

$$SPC(W) = \sum_{k=1-L}^{L-1} g_b(\chi^*[n] + \beta^*[n]). \qquad (29)$$

The normalization in (16) gives

$$\sum_{n=1-L}^{L-1} g_b[n] \left[ g_c[n] + \delta[n] \right] = 1, \qquad (30)$$

if

$$v[n] = \delta[n], \qquad (31)$$

which it is if $\psi(t)$ is a root raised cosine pulse.

When searching for a good coded modulation scheme we use the algorithm described in section 2. In step 2 we then solve the LP for different $c[n]$ and select the optimal. We use a set of 30 filters each of length 3. Some results are given in table 3, comparisons are made against complex valued OPRS with equal $L$. It can be seen that the gains are small, however simulations shows that decoding complexity is much worse than both OPRS and COPRS.

It may appear unfear to compare to OPRS with equal length $L$ OPRS since $h_{12}(t)$ consists of $L+2$ taps. However, the general case of 4–dimensional OPRS has two filters each of length $L$ while this suboptimal variant consists of one $L$–tap filter ($b[n]$) and one 3–tap filter ($c[n]$). So the degrees of freedom in the optimization is much less than in the general case, but gains are eventhough possible.

## 5. CONCLUSIONS

A previously known coded modulation scheme has been extended. It was first concatenated with a low memory convolutional encoder. The results of this are very good: significant gains in Euclidian minimum distance and only small increase in decoding complexity. Also it was necessary to increase the alphabet size.

We also extended the scheme to multi dimensions. No linear formulation for this case was found. Instead we derived a suboptimal linear formulation. The results are not as good as COPRS: small gains and a large increase in decoding complexity. It is interesting to observe that the extension of TCM to multi dimensions (see [8], chapter 5) leads to similar .3–.7 dB gains as multi dimensional PRS achieves.

## A. NUMERICAL RESULTS FOR COPRS

In table 1 to table 6 we give some minimum distances for COPRS, the comparisons are made against OPRS with equal $L$.

Table 1: Obtained minimum distances for COPRS. The optimal convolutional encoder is given in brackets. R=1, r=1, 99 % SPC, 6 taps, $\nu = 3$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .50 | 2.00 | 3.21 (5,2) | 2.05 |
| .46 | 2.00 | 2.98 (5,2) | 1.73 |
| .42 | 2.00 | 2.36 (5,2) | 0.72 |
| .38 | 1.95 | 2.15 (5,2) | 0.42 |
| .34 | 1.41 | 1.89 (5,2) | 1.27 |
| .30 | 1.20 | 1.77 (5,2) | 1.69 |
| .26 | 0.95 | 1.53 (5,2) | 1.61 |

Table 2: Obtained minimum distances for COPRS. The optimal convolutional encoder is given in brackets. R=1, r=1, 99 % SPC, 6 taps, $\nu = 4$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .50 | 2.00 | 3.69 (17,6) | 2.66 |
| .46 | 2.00 | 3.49 (17,6) | 2.42 |
| .42 | 2.00 | 3.15 (17,6) | 1.97 |
| .38 | 1.95 | 2.58 (17,2) | 1.22 |
| .34 | 1.41 | 2.17 (13,6) | 1.87 |
| .30 | 1.20 | 1.79 (17,6) | 1.74 |

Table 3: Obtained minimum distances for COPRS. The optimal convolutional encoder is given in brackets. R=1, r=1, 99 % SPC, 6 taps, $\nu = 5$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .50 | 2.00 | 3.99 (25,14) | 3.00 |
| .46 | 2.00 | 3.88 (33,10) | 2.88 |
| .42 | 2.00 | 3.40 (37,14) | 2.31 |
| .38 | 1.95 | 2.78 (27,2) | 1.54 |
| .34 | 1.41 | 2.20 (23,10) | 1.93 |

Table 4: Obtained minimum distances for COPRS. The optimal convolutional encoder is given in brackets. R=2, r=1, 99 % SPC, 8 taps, $\nu = 5$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .24 | 0.84 | 1.90 (23,4) | 3.55 |
| .22 | 0.80 | 1.54 (23,4) | 2.84 |
| .20 | 0.80 | 1.22 (23,4) | 1.83 |
| .18 | 0.70 | 0.92 (23,4) | 1.18 |
| .16 | 0.56 | 0.73 (23,4) | 1.16 |

Table 5: Obtained minimum distances for COPRS. The optimal convolutional encoder is given in brackets. R=2, r=1, 99.9 % SPC, 8 taps, $\nu = 5$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .3 | 0.99 | 1.93 (23,4) | 2.88 |
| .28 | 0.81 | 1.52 (23,4) | 2.73 |
| .26 | 0.80 | 1.04 (23,4) | 1.14 |
| .24 | 0.80 | 0.90 (23,4) | 0.51 |
| .22 | 0.80 | 0.83 (23,4) | 0.16 |
| .20 | 0.68 | 0.75 (23,4) | 0.45 |
| .18 | 0.45 | 0.53 (23,4) | 0.73 |
| .16 | 0.22 | 0.27 (23,4) | 0.82 |
| .14 | 0.12 | 0.17 (23,4) | 1.37 |

Table 6: Obtained minimum distances for COPRS. Only a single encoder was tested. R=2, r=2, 99 % SPC, 6 taps, $\nu = 3$.

| NBW | OPRS $d^2_{\min}$ | COPRS $d^2_{\min}$ | gain (dB) |
|---|---|---|---|
| .25 | 0.83 | 1.32 | 1.86 |
| .24 | 0.80 | 1.30 | 2.11 |
| .23 | 0.80 | 1.26 | 1.97 |
| .22 | 0.80 | 1.18 | 1.69 |
| .21 | 0.80 | 1.12 | 1.46 |
| .20 | 0.80 | 1.07 | 1.26 |

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