## Progressive Algebraic Soft-Decision Decoding of Reed-Solomon Codes

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## Outline

- Introduction
- Progressive ASD (PASD) algorithm
- Validity analysis
- Complexity analysis
- Error-correction performance
- Conclusions


## I. Introduction of list decoding

- Decoding philosophy evolution of an $(n, k)$ RS code

Unique decoding


## I. Overview of Enc. \& Decd.

- Encoding
- Given a message polynomial: $u(x)=u_{0}+u_{1} x+\cdots+u_{k-1} x^{k-1} \quad\left(u_{i} \in \operatorname{GF}(q)\right)$
- Generate the codeword of an $(n, k) \mathrm{RS}$ code

$$
\mathbf{c}=\left(c_{0}, c_{1}, \ldots, c_{n-1}\right)=\left(u\left(\alpha_{0}\right), u\left(\alpha_{1}\right), \ldots, u\left(\alpha_{n-1}\right)\right) \quad\left(\alpha_{i} \in \operatorname{GF}(q) \backslash\{0\}\right)
$$

- Decoding



## I. Perf. of AHD and ASD

- Algebraic hard-decision decoding (AHD) [Guruwammi99] (-GS Alg)
- Algebraic soft-decision decoding (ASD) [Koetter03] (-KV Alg)
- Advantage on error-correction performance

Performance of RS $(63,31)$ over AWGN channel


## I. Introduction

- Price to pay decoding complexity



## I. Inspirations

- The algebraic soft decoding is of high complexity. It is mainly due to the iterative interpolation process;
- A modernized thinking - the decoding should be flexible (i.e., channel dependent).

E.g., the belief propagation algorithm


Iterative proc.
そ

## II. A Graphical Introduction

$$
\operatorname{ASD}(l=5) \quad \longrightarrow \text { PASD }(l=1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5)
$$


$L=\left\{c_{5}, c_{6}, c_{7}, c_{9}, c_{10}\right\}$
$|L|$ - factorization output list size


Enlarging the decoding radius progressively $\rightarrow$ Enlarging the factorization OLS progressively

## II . Decoding architecture


$v$-iteration index;
$l_{v}$-- designed OLS at each iteration;
$l_{T}$-- designed maximal OLS ( $\sim$ the maximal complexity that the system can tolerate);
$l^{\prime}-$ step size for updating the OLS, $l_{v+1}=l_{v}+l^{\prime}$;

## II. Progressive approach

- Enlarge the decoding radius $\rightarrow$ Enlarge the OLS
- Progressive decoding


Series of $Q$ polys.: $Q^{(1)}, Q^{(2)}, \ldots \ldots, Q^{(v-1)}, Q^{(v)}, \ldots \ldots, Q^{(T)}$

Question: Can the solution of $Q^{(v)}$ be found based on the knowledge of $Q^{(v-1)}$ ?

## II. Incremental interpolation constraints

- Multiplicity $m_{i j} \sim$ interpolated point $\left(x_{j}, \alpha_{i}\right)$
- Given a polynomial $Q(x, y), m_{i j}$ implies $\frac{1}{2} m_{i j}\left(m_{i j}+1\right) \quad$ constraints of

$$
\left.\mathcal{D}_{r, s}(Q(x, y))\right|_{x=x_{j}, y=\alpha_{i}}=\sum_{a \geq r, b \geq s}\binom{a}{r}\binom{b}{s} Q_{a b} x_{j}^{a-r} \alpha_{i}^{b-s}=0 \quad\left(r+s<m_{i j}\right)
$$

- Definition 1: Let $\Lambda\left(m_{i j}\right)$ denote a set of interpolation constraints $(r, s)_{i j}$ indicated by $m_{i j}$, then $\Lambda(\mathrm{M})$ denotes a collection of all the sets $\Lambda\left(m_{i j}\right)$ defined by the entry $m_{i j}$ of M

$$
\Lambda(\mathrm{M})=\left\{\Lambda\left(m_{i j}\right), \forall m_{i j} \in \mathrm{M}\right\}
$$

- Example: $\mathbf{M}=\left[\begin{array}{ccc}\mathbf{2} & \mathbf{O} & \mathbf{O} \\ \mathbf{O} & \mathbf{1} & \mathbf{1} \\ \mathbf{1} & 2 & \mathbf{O} \\ \mathbf{O} & \mathbf{O} & \mathbf{1}\end{array}\right] \Longrightarrow \Lambda(\mathbf{M})=\begin{gathered}\left\{(0,0)_{00},(1,0)_{00},(0,1)_{00},(0,0)_{11},\right. \\ (0,0)_{12},(0,0)_{20},(0,0)_{21},(1,0)_{21}, \\ \left.(0,1)_{21},(0,0)_{32}\right\}\end{gathered}$


## II. Incremental Interp. Constr.

- Definition 2: Let $m_{i j}{ }^{v-1}$ and $m_{i j}{ }^{v}$ denote the entries of matrix $\mathrm{M}_{v-1}$ and $\mathrm{M}_{v}$, the incremental interpolation constraints introduced between the matrices are defined as a collection of all the residual sets between $\Lambda\left(m_{i j}{ }^{\nu}\right)$ and $\Lambda\left(m_{i j}{ }^{v-1}\right)$ as:

$$
\Lambda\left(\Delta \mathrm{M}_{v}\right)=\left\{\Lambda\left(\mathrm{M}_{v}\right) \backslash \Lambda\left(\mathrm{M}_{v-1}\right)\right\}=\left\{\Lambda\left(m_{i j}^{v}\right) \backslash \Lambda\left(m_{i j}^{v-1}\right), \forall m_{i j}^{v} \in \mathrm{M}_{v} \text { and } m_{i j}^{v-1} \in \mathrm{M}_{v-1}\right\}
$$

- Example: $M_{2}=\left[\begin{array}{ccc}2 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 2 & 0 \\ 0 & 0 & 1\end{array}\right]$

$$
\Lambda\left(\mathrm{M}_{2}\right)=\left\{\begin{array}{l}
\left\{(0,0)_{00},(1,0)_{00},(0,1)_{00}\right. \\
(0,0)_{11},(0,0)_{12},(0,0)_{20}, \\
(0,0)_{21},(1,0)_{21},(0,1)_{21}, \\
\left.(0,0)_{32}\right\}
\end{array}\right.
$$

| $\mathrm{M}_{1}=\left[\begin{array}{lll}1 & 0 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 1\end{array}\right]$ |  |
| :---: | :---: |
|  | $\begin{aligned} & 0)_{00},(0,0)_{12}, \\ & \left.0)_{20},(0,0)_{21},(0,0)_{32}\right\} \end{aligned}$ <br> 5 constraints |
| $\begin{aligned} & \left\{(1,0)_{00},(0,1)_{00},(0,0)_{11},\right. \\ & \left.(1,0)_{21},(0,1)_{21}\right\} \end{aligned}$ | 5 constraints |

## II. Progressive Interpolation

- A big chunk of interpolation task $\Lambda\left(\mathrm{M}_{T}\right)$ can be sliced into smaller pieces.

- $\Lambda\left(\mathrm{M}_{T}\right)=\Lambda\left(\Delta \mathrm{M}_{1}\right) \cup \Lambda\left(\Delta \mathrm{M}_{2}\right) \cup \cdots \cup \Lambda\left(\Delta \mathrm{M}_{v}\right) \cup \cdots \cup \Lambda\left(\Delta \mathrm{M}_{T}\right)$.
- $\Lambda\left(\Delta \mathrm{M}_{v}\right)$ defines the interpolation task of iteration $v$.


## II. Incremental Computations

- Review on the interpolation process - iterative polynomial construction
- Given $\mathrm{M}_{v}$, the interpolation constraints are $\Lambda\left(\mathrm{M}_{v}\right)$
- The polynomial group is: $\mathbf{G}_{v}=\left\{g_{0}, g_{1}, \ldots, g_{v}\right\},\left(\operatorname{deg}_{y} g_{v}=l_{v}\right)$
- The iterative process

$$
\begin{gathered}
\text { For }(r, s)_{i j} \in \Lambda\left(\mathrm{M}_{v}\right) \\
f_{(r, s)_{i j}}=\min \left\{g_{t} \mid \mathcal{D}_{(r, s)_{i j}}\left(g_{t}\right) \neq 0\right\} .
\end{gathered}
$$

For each $g_{t} \in \mathbf{G} v$
$g_{t}= \begin{cases}g_{t}, & \text { if } \mathcal{D}_{(r, s)_{i j}}\left(g_{t}\right)=0 \\ {\left[g_{t}, f_{(r, s)_{i j}}\right]_{D},} & \text { if } \mathcal{D}_{(r, s)_{i j}}\left(g_{t}\right) \neq 0 \text { and } g_{t} \neq f_{(r, s)_{i j}} \\ {\left[x f_{(r, s)_{i j}}, f_{(r, s)_{i j}}\right]_{D},} & \text { if } f_{(r, s)_{i j}},\end{cases}$

Finally, $Q^{(v)}=\min \left\{g_{t} \mid g_{t} \in \mathbf{G}_{v}\right\}$

## II. Incremental Computations

- From iteration $v-1$ to $v . .$.
- The progressive interpolation can be seen as a progressive polynomial group expansion which consists of two successive stages.
- Let $\tilde{\mathbf{G}}_{v-1}=\left\{\tilde{g}_{0}, \tilde{g}_{1}, \ldots, \tilde{g}_{v-1}\right\}$ be the outcome of iteration $v-1$.
- During the generation of $\tilde{\mathbf{G}}_{v-1}$, a series of $f_{(r, s)_{i j}}$ with $(r, s)_{i j} \in \Lambda\left(\mathrm{M}_{v-1}\right)$ are identified and stored.
- Expansion I: expand the number of polynomials of the group

$$
\Delta \mathbf{G}_{v}=\left\{g_{l_{v-1}+1}, \ldots, g_{l_{v}}\right\}=\left\{y^{l_{v-1}+1}, \ldots, y^{l_{v}}\right\}
$$

- Polynomials of $\Delta \mathbf{G}_{v}$ perform interpolation w.r.t. constraints of $\Lambda\left(\mathrm{M}_{v-1}\right)$;
- Polynomials $f_{(r, s)_{i j}}$ are re-used for the update of $\Delta \mathbf{G}_{v}$.
- Let $\Delta \widetilde{\mathbf{G}}_{v}$ be the updated outcome of $\Delta \mathbf{G}_{v}$ and $\mathbf{G}_{v}=\tilde{\mathbf{G}}_{v-1} \cup \Delta \tilde{\mathbf{G}}_{v}$.


## II. Incremental Computations

- Expansion II: expand the size of polynomials of the group $\mathbf{G}_{v}$
- Polynomials of $\mathbf{G}_{v}$ will now perform interpolation w.r.t. the incremental constraints $\Lambda\left(\Delta \mathrm{M}_{v}\right)$, yielding $\widetilde{\mathbf{G}}_{v}$.
- Finally, $Q^{(v)}(x, y)=\min \left\{\tilde{g}_{t} \mid \tilde{g}_{t} \in \tilde{\mathbf{G}}_{v}\right\}$
- $\rightarrow$ Visualize the polynomial group expansion Expansion I E.g., $l_{v}=5$
$\begin{array}{llllll}g_{1} & g_{2} & g_{3} & g_{4} & g_{5} & g_{6}\end{array}$
$\begin{array}{llllll}g_{1} & g_{2} & g_{3} & g_{4} & g_{5} & g_{6}\end{array}$
 ASD



## II. Progressive Interpolation

- The process of progressive interpolation
- $\quad \mathrm{M}_{1}, \quad \mathrm{M}_{2}, \quad \mathrm{M}_{3}, \ldots, \quad \mathrm{M}_{v-1}, \quad \mathrm{M}_{v}, \ldots, \quad \mathrm{M}_{T-1}, \quad \mathrm{M}_{T}$


$$
\text { If } Q^{(v)}(x, u(x))=0 \text {, the decoding will be terminated. }
$$

- Multiple factorizations are carried out in order to determine whether $u(x)$ has been found!


## III. Validity Analysis

- For any two $\left(r_{1}, s_{1}\right)_{i j 1 j}$ and $\left(r_{2}, s_{2}\right)_{i 2 j 2}$ of $\Lambda\left(\mathrm{M}_{T}\right)$ :

$$
\left(r_{1}, s_{1}\right)_{i j 11} \Longrightarrow\left(r_{2}, s_{2}\right)_{i 2 j 2} \Longleftrightarrow=\left(r_{2}, s_{2}\right)_{i 2 j 2} \Longrightarrow\left(r_{1}, s_{1}\right)_{i j 11}
$$

- The algorithm imposes a progressive interpolation order

- The satisfied $(r, s)_{i j}$.


## III. Validity Analysis

- Decoding with an OLS of $l_{v}$, the solution $Q(x, y)$ is seen as the minimal candidate chosen from the cumulative kernel $\overline{\mathcal{K}_{\mathcal{C}\left(\mathrm{M}_{v}\right)}}$

$$
\begin{aligned}
& \overline{\mathcal{K}_{\mathcal{C}\left(\mathrm{M}_{v}\right)}}=\left\{Q \in \mathbb{F}_{q}[x, y] \mid \mathcal{D}_{w}(Q)=0 \forall w \in \Lambda\left(\mathrm{M}_{v}\right), \operatorname{deg}_{y} Q \leq l_{v}\right\} \\
& Q(x, y)=\min \left\{Q \in \overline{\mathcal{K}_{\mathcal{C}\left(\mathrm{M}_{v}\right)}}\right\}
\end{aligned}
$$

- For both of the algorithms:

$$
\Lambda\left(\mathrm{M}_{v}\right)=\Lambda\left(\Delta \mathrm{M}_{1}\right) \cup \Lambda\left(\Delta \mathrm{M}_{2}\right) \cup \cdots \cup \Lambda\left(\Delta \mathrm{M}_{v}\right)
$$

the same set of constraints are defined for the cumulative kernel;

- Consequently, they will offer the same solution of $Q(x, y)$.


## III. Validity Analysis

- In the end of Expansion $I, \quad \mathbf{G}_{v}=\widetilde{\mathbf{G}}_{v-1} \cup \Delta \widetilde{\mathbf{G}}_{v}$
- Can $\tilde{\mathbf{G}}_{v-1}$ and $\Delta \widetilde{\mathbf{G}}_{v}$ be found separately?
- Recall the polynomial updating rules

$$
g_{t}= \begin{cases}g_{t}, & \text { if } \mathcal{D}_{(r, s)_{i j}}\left(g_{t}\right)=0 \\ {\left[g_{t}, f_{\left.(r, s)_{i j}\right)^{2}},\right.} & \text { if } \mathcal{D}_{(r, s)_{i j}}\left(g_{t}\right) \neq 0 \text { and } g_{t} \neq f_{(r, s)_{i j}} \\ {\left[x f_{(r, s)_{i j}} f_{\left.(r, s)_{i j}\right)},\right.} & \text { if } f_{(r, s)_{i j},},\end{cases}
$$

- The minimal polynomial $f_{(r, s)_{i j}}$ defines the solution of one round of poly. update w.r.t. $(r, s)_{i j}$.
- If such a group expansion procedure does not change the identity of $f_{(r, s)_{i j}}$, $\widetilde{\mathbf{G}}_{v-1}$ and $\Delta \widetilde{\mathbf{G}}_{v} \quad$ can indeed be found separately.


## III. Validity Analysis

- Lemma 1: For all the polynomials $f_{(r, s)_{i j}}$ with $(r, s)_{i j} \in \Lambda\left(\mathrm{M}_{v-1}\right)$, we have

$$
\operatorname{lod}\left(f_{(r, s)_{i j}}\right)<\operatorname{lod}\left(y^{l_{v-1}+1}\right) . \Longrightarrow\left(f_{(r, s)_{i j}}<y^{l_{v-1}+1}\right)
$$

- Expansion I: update $\Delta \mathbf{G}_{v}$ to $\Delta \tilde{\mathbf{G}}_{v}$ w.r.t. constraint of $\Lambda\left(\mathrm{M}_{v-1}\right)$

$$
\text { For }(r, s)_{i j} \in \Lambda\left(\mathbf{M}_{v-1}\right)\left\{\begin{array}{l}
\text { No update is required } \\
\text { Update is required } \begin{cases}f_{(r, s)_{i j}} & \text { is in memory, } \\
\text { Since } f_{(r, s)_{i j}}<g^{*}\left(\text { of } \Delta \mathbf{G}_{v}\right) \\
f_{(r, s)_{i j} \text { will be re-used }}\end{cases} \\
f_{(r, s)_{i j}} \begin{array}{l}
\text { is not in memory, it will be } \\
\text { picked up from } \Delta \mathbf{G}_{v .}
\end{array}
\end{array}\right.
$$

- The identity of the existing $f_{(r, s)_{i j}}$ is left unchanged. Consequently, the solution of $\tilde{\mathbf{G}}_{v-1}$ remains intact.
- Therefore, $\mathbf{G}_{v}=\tilde{\mathbf{G}}_{v-1} \cup \Delta \tilde{\mathbf{G}}_{v}$


## IV. Complexity Analysis

- Average decoding complexity - average number of finite field arithmetic operation for decoding one codeword frame;
- $\mathcal{P}_{l_{v}}$--- the probability of the decoder is performing a successful decoding with an OLS of $l_{v}$;
$\mathcal{O}_{l_{v}---}$ the decoding complexity with an OLS of $l_{v}$;
- The average decoding complexity is:

$$
\mathcal{O}_{\text {PASD }}=\underbrace{\sum_{v=1}^{T} \mathcal{P}_{l_{v}} \mathcal{O}_{l_{v}}}_{\text {Decoding succ. }}+\underbrace{\left(1-\sum_{v=1}^{T} \mathcal{P}_{l_{v}}\right) \mathcal{O}_{l_{T}}}_{\text {Decoding fail. }}
$$

- $\mathcal{O}_{\text {PASD }}$ is now channel dependent!


## IV. Complexity Analysis

- Theorem 2: The decoding complexity of running the PASD algorithm with an OLS of $l_{v}$ is:

$$
\mathcal{O}_{l_{v}}=O\left(\mathcal{C}^{2}\left(\mathrm{M}_{v}\right)\left(l_{v}+1\right)\right) .
$$

where $\mathcal{C}(\mathrm{M})=|\Lambda(\mathrm{M})|=\frac{1}{2} \sum_{i=0}^{q-1} \sum_{j=0}^{n-1} m_{i j}\left(m_{i j}+1\right)$

- $\mathcal{O}_{l_{v}}$ consists of $\mathcal{O}_{l_{v}}^{\text {int }}$ and $\mathcal{O}_{l_{v}}^{\text {fac }}$

$$
\text { since } k v \ll \mathcal{C}\left(\mathrm{M}_{v}\right)
$$

$$
\begin{aligned}
& \mathcal{O}_{l_{v}}^{\text {int }}=O\left(\mathcal{C}\left(\mathrm{M}_{v}\right)\left(\mathcal{C}\left(\mathrm{M}_{v}\right)+1\right)\left(l_{v}+1\right)\right) \cong O\left(\mathcal{C}^{2}\left(\mathrm{M}_{v}\right)\left(l_{v}+1\right)\right) \\
& \mathcal{O}_{l_{v}}^{\text {fac }}=O\left(k \sum_{\eta=1}^{v}\left(\mathcal{C}\left(\mathrm{M}_{\eta}\right)+1\right) l_{\eta}\right)<O\left(k v\left(\mathcal{C}\left(\mathrm{M}_{v}\right)+1\right) l_{v}\right) \\
& \ll \mathcal{C}\left(\mathrm{M}_{v}\right) \\
& \mathcal{O}_{l_{v}}^{\text {fac } \ll \mathcal{O}_{l_{v}}^{\text {int }}} \\
& \mathcal{O}_{l_{v}} \cong \mathcal{O}_{l_{v}}^{\text {int }}
\end{aligned}
$$

## IV. Complexity Analysis

- Corollary 3: When $l_{v}$ is sufficiently large, the decoding complexity $\mathcal{O}_{l_{v}}$ becomes:

$$
\mathcal{O}_{l_{v}}=O\left(\frac{(k-1)^{2}}{4}\left(l_{v}^{5}+l_{v}^{4}\right)\right)
$$

- The decoding complexity increases exponentially with the OLS (dominant exponential factor of 5);
- The decoding complexity is quadratic in the dimension of the code $k$. The decoding complexity will be smaller for a low rate code.


## IV. Complexity Analysis

- Theorem 4: The probability of the PASD algorithm performing a successful decoding with an OLS of $l_{v}$ is given as:

$$
\mathcal{P}_{l_{v}}=\operatorname{Pr}\left[S_{\mathrm{M}_{v}}(\bar{c})>\Delta_{1, k-1}\left(\mathcal{C}\left(\mathrm{M}_{v}\right)\right) \text { and } S_{\mathrm{M}_{v-1}}(\bar{c}) \leq \Delta_{1, k-1}\left(\mathcal{C}\left(\mathrm{M}_{v-1}\right)\right)\right]
$$

- The probability that the algorithm terminates at iteration $v$.



## IV. Complexity Analysis

- Determining a closed form expression of $\mathcal{P}_{l_{v}}$ turns out to be hard;
- Motivation of the analysis: link $\mathcal{P}_{l_{v}}$ with $\Pi$ ( $\sim$ channel SNR);
- Define $\mathcal{L}=\left\{l \left\lvert\, l>\frac{2+\frac{\sqrt{n \gamma}}{\sqrt{\sum_{i, j} \pi_{i j}^{2}}}}{2 \gamma\left[1-\sqrt{k-1} \Phi_{\Pi}(\bar{c})\right]}\right.\right\}$, where $\gamma=\frac{k-1}{n}$ and $\Phi_{\Pi}(\bar{c})=\frac{\sqrt{\sum_{i, j} \pi_{i j}^{2}}}{S_{\Pi}(\bar{c})}$,
with OLS greater than the above threshold, successful decoding can be guaranteed.
- We therefore interpret $\mathcal{P}_{l_{v}}$ as:

$$
\mathcal{P}_{l_{v}} \cong \operatorname{Pr}\left[l_{v}=\min \mathcal{L}\right] .
$$

## IV. Complexity Analysis

- Study the possible quantization of the OLS threshold

$$
\frac{2+\frac{\sqrt{n \gamma}}{\sqrt{\sum_{i, j} \pi_{i j}^{2}}}}{2 \gamma\left[1-\sqrt{k-1} \Phi_{\Pi}(\bar{c})\right]}
$$

- AWGN channel, we vary the SNR ...

In case of a 'bad' channel (e.g., SNR $\rightarrow-\infty$ ): $\pi_{i j} \cong 1 / q$ for all $\pi_{i j} \in \Pi$.

$$
\sqrt{\sum_{i, j} \pi_{i j}^{2}} \cong \sqrt{\frac{n}{q}}: \quad S_{\Pi}(\bar{c}) \cong \frac{n}{q} \quad \Phi_{\Pi}(\bar{c}) \cong \sqrt{\frac{q}{n}}
$$

In case of a 'good' channel (e.g., SNR $\rightarrow \hat{+\infty}$ ): $\begin{aligned} & \pi_{i j} \cong 1 \text { if } i=i_{j} \text {, and } \pi_{i j} \cong 0 ~\end{aligned}$

$$
\sqrt{\sum_{i, j} \pi_{i j}^{2}} \cong \sqrt{n} \quad S_{\Pi}(\bar{c}) \cong n \quad \Phi_{\Pi}(\bar{c}) \cong \frac{1}{\sqrt{n}}
$$

- By refining $\frac{1}{\sqrt{n}} \leq \Phi_{\Pi}(\bar{c})<\frac{1}{\sqrt{k-1}}$,
we can see the OLS threshold is a decreasing function of SNR.
$\underline{\text { Recall }} \mathcal{P}_{l_{v}} \cong \operatorname{Pr}\left[l_{v}=\min \mathcal{L}\right]_{\underline{-}}, \mathcal{L}=\left\{l \left\lvert\, l>\frac{2+\frac{\sqrt{n \gamma}}{\sqrt{\sum_{i, j} \pi_{2 j}^{2}}}}{2 \gamma\left[1-\sqrt{k-1} \Phi_{\Pi}(\bar{c})\right]}\right.\right\}$
$\mathcal{P}_{l_{v}}$ will be in favor of smaller $l_{v}$ values by increasing SNR!


## IV. Complexity Analysis

- Recall the average decoding complexity definition:

$$
\mathcal{O}_{\mathrm{PASD}}=\sum_{v=1}^{T} \mathcal{P}_{l_{v}} \mathcal{O}_{l_{v}}+\left(1-\sum_{v=1}^{T} \mathcal{P}_{l_{v}}\right) \mathcal{O}_{l_{T}}
$$



## IV. Simulation Statistics

- $\mathcal{P}_{l_{v}} \sim \operatorname{SNR}$ for the $(63,47) \mathrm{RS}$ code with $l_{1}=1, l^{\prime}=1$ and $l_{T}=5$
- AWGN channel

| $\mathcal{P}_{l_{v}}(\%)$ | SNR (dB) | 2 | 3 | 4 | 5 | 6 | 7 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathcal{P}_{l_{1}}$ | 0.00 | 0.00 | 3.71 | 32.54 | 78.55 | 97.13 | 89.87 |
| $\mathcal{P}_{l_{2}}$ | 0.00 | 1.51 | 28.47 | 56.30 | 21.25 | 2.87 | 0.13 |
| $\mathcal{P}_{l_{3}}$ | 0.00 | 1.61 | 15.92 | 6.59 | 0.17 | 0.00 | 0.00 |
| $\mathcal{P}_{l_{4}}$ | 0.00 | 1.23 | 9.68 | 1.95 | 0.02 | 0.00 | 0.00 |
| $\mathcal{P}_{l_{5}}$ | 0.00 | 1.22 | 5.54 | 0.77 | 0.00 | 0.00 | 0.00 |

## IV. Simulation Results

- $\mathcal{O}_{\text {PASD }} \sim \operatorname{SNR}$ for the $(63,47) \mathrm{RS}$ code with $l_{T}=3,5,7$.
- AWGN channel



## IV. Simulation Results

- $\mathcal{O}_{\text {PASD }} \sim \operatorname{SNR}$ for the $(15,11)$ and $(15,5) \operatorname{RS}$ codes with $l_{T}=1,3,5,10$
- AWGN channel



## V. Error-Correction Performance

- PASD ~ ASD with same decoding parameter $l_{T}$;
- For PASD, decoding output is validated by CRC code;
- For ASD, decoding output is validated by the ML criterion;
- For the $(63,47)$ RS code, over AWGN channel:



## VI. Conclusions

- A progressive algebraic soft-decision decoding approach;
- Two key steps of PASD: progressive reliability transform \& progressive interpolation;
- Enables the complexity dominant interpolation process to be performed in an iterative manner, and the incremental computation between iterations is possible;
- The average decoding complexity of the PASD algorithm is channel dependent and hence it has been optimized according to the needs;
- Error-correction performance is also preserved.
- A larger system memory is required.


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