A Locally Optimal Design Algorithm for Block-Based Multi-Hypothesis Motion-Compensated Prediction

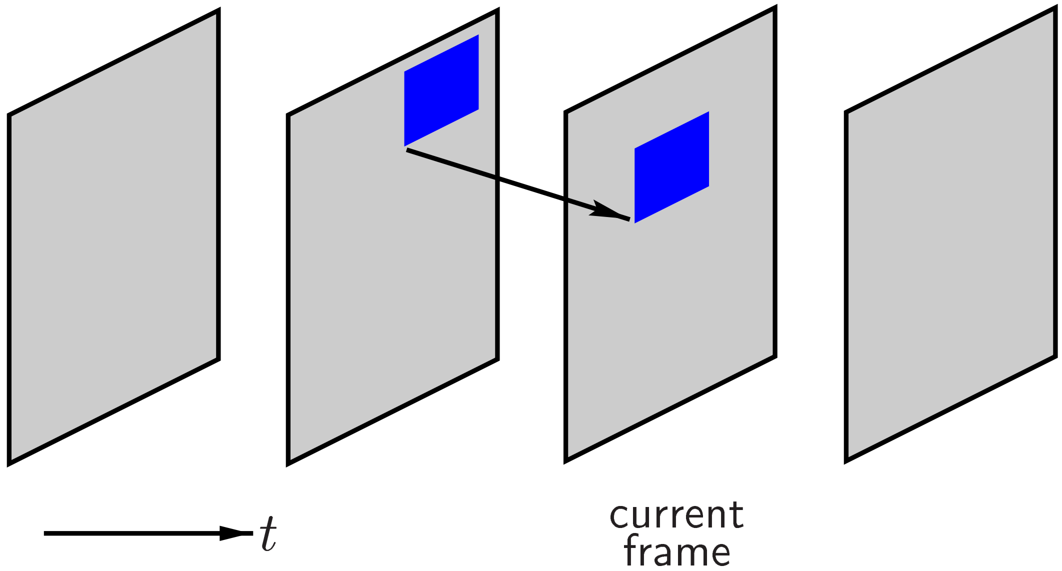
Markus Flierl, Thomas Wiegand, Bernd Girod

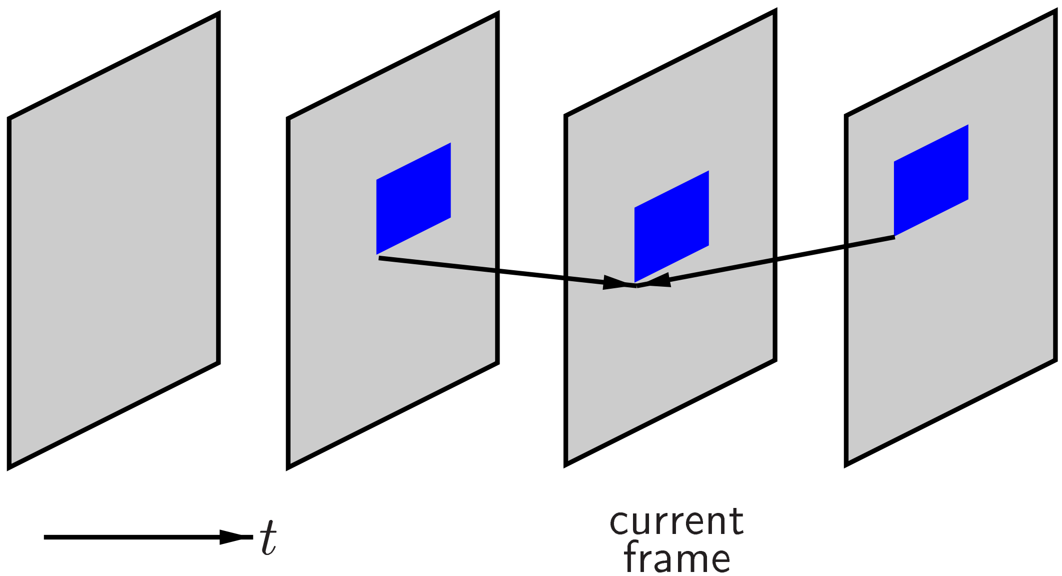
Telecommunications Laboratory

University of Erlangen-Nuremberg

Erlangen, Germany

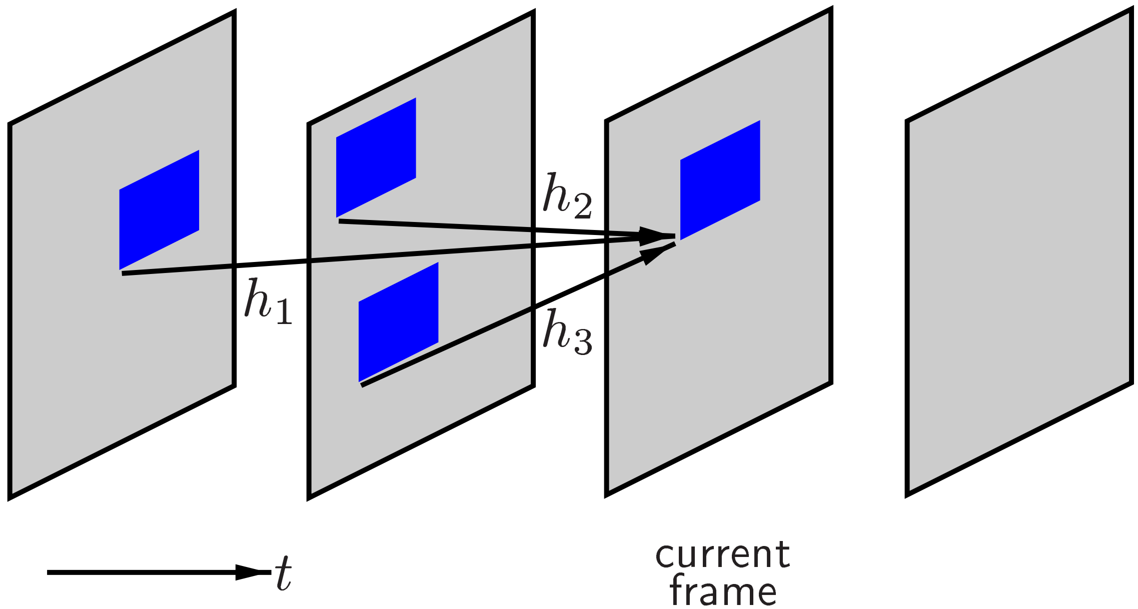
Motivation





How about combining an arbitrary number of hypotheses?

Multi-Hypothesis Motion-Compensated Prediction



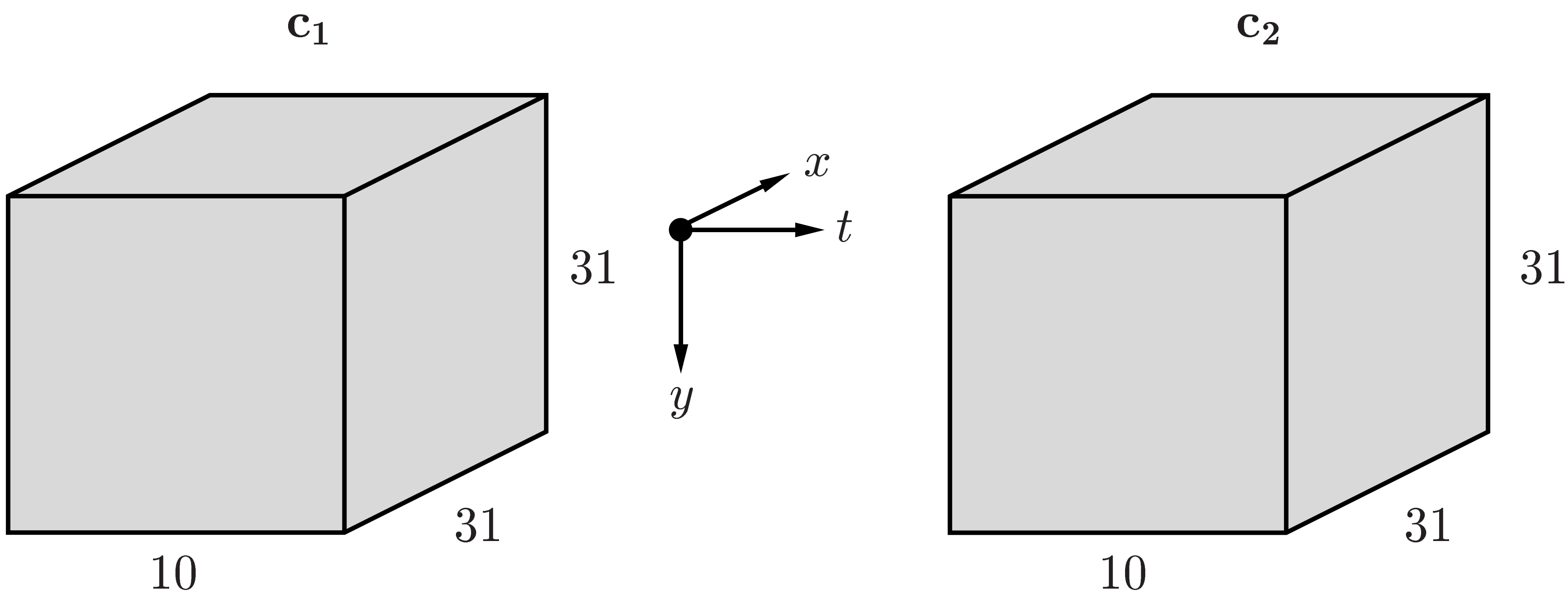
Each hypothesis $\mathbf{c}_\nu$ is assigned a relative spatio-temporal displacement $(\mathbf{\Delta x}_\nu, \mathbf{\Delta y}_\nu, \mathbf{\Delta t}_\nu)$ and is weighted by a constant scalar h_ν.

Hypotheses are selected only from previous frames!

Multi-hypothesis: Array of hypotheses

How to Select an Optimal Multi-Hypothesis?

Example: 2-Hypothesis



3-dimensional search space for each hypothesis

Full search for a n-hypothesis:

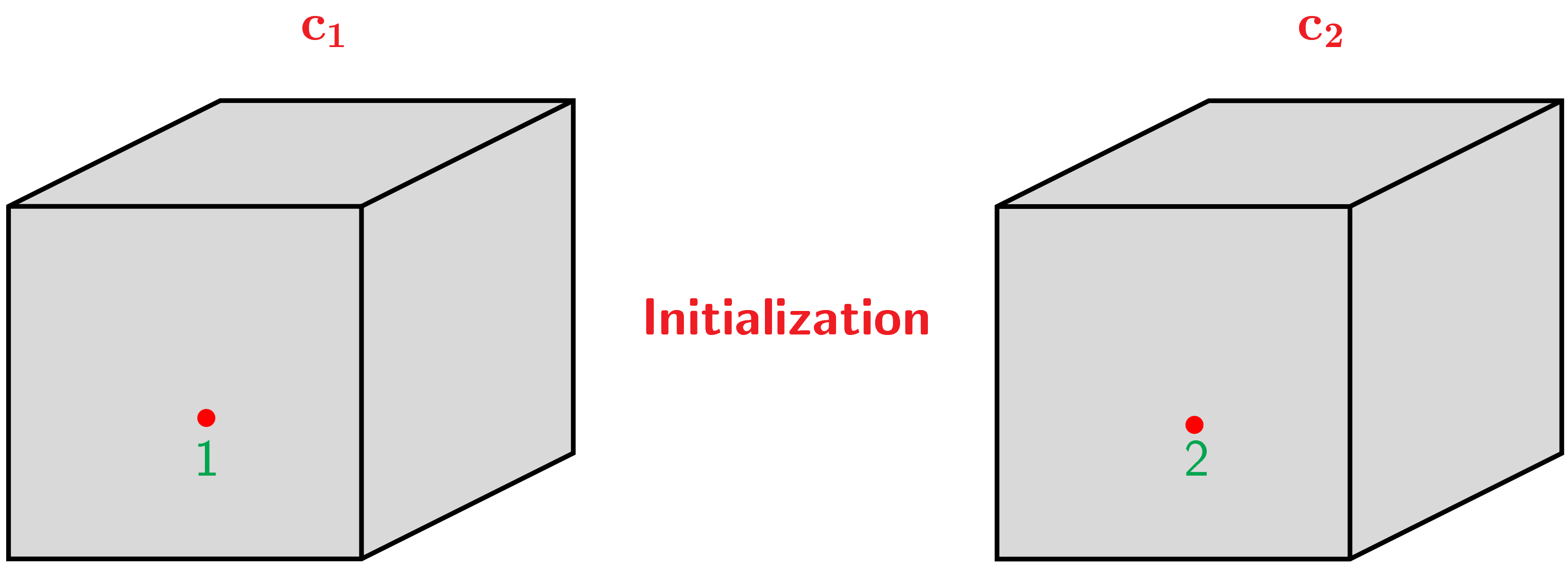
Complexity $\sim (\cdot)^n$

Too demanding!!

$\hookrightarrow$ Successive improvement of n optimal conditional solutions.

Hypothesis Selection Algorithm I

An iterative algorithm, which is inspired by the *Iterated Conditional Modes*.

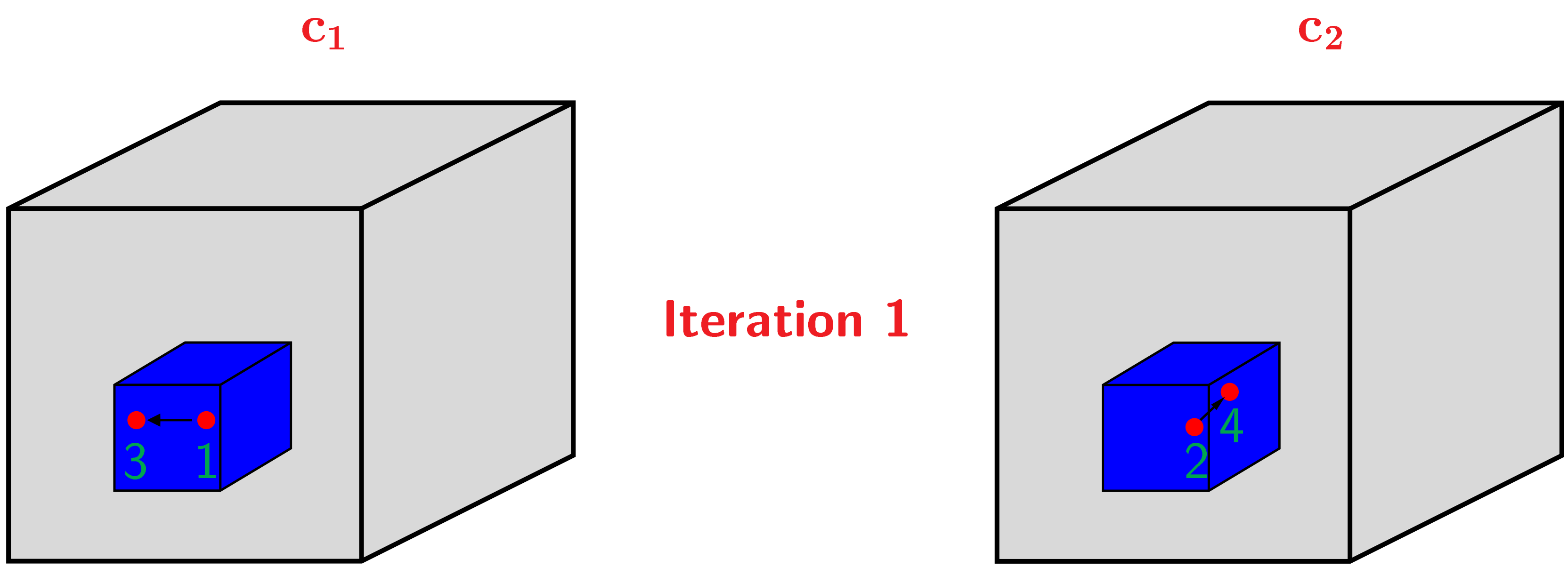


⇒ Find the optimal 1-hypothesis in search space.

⇒ Repeat the optimal 1-hypothesis n times to generate the initial n-hypothesis.

Hypothesis Selection Algorithm II

3-dimensional conditional search space: $[-b, b] \times [-b, b] \times [-b, b]$

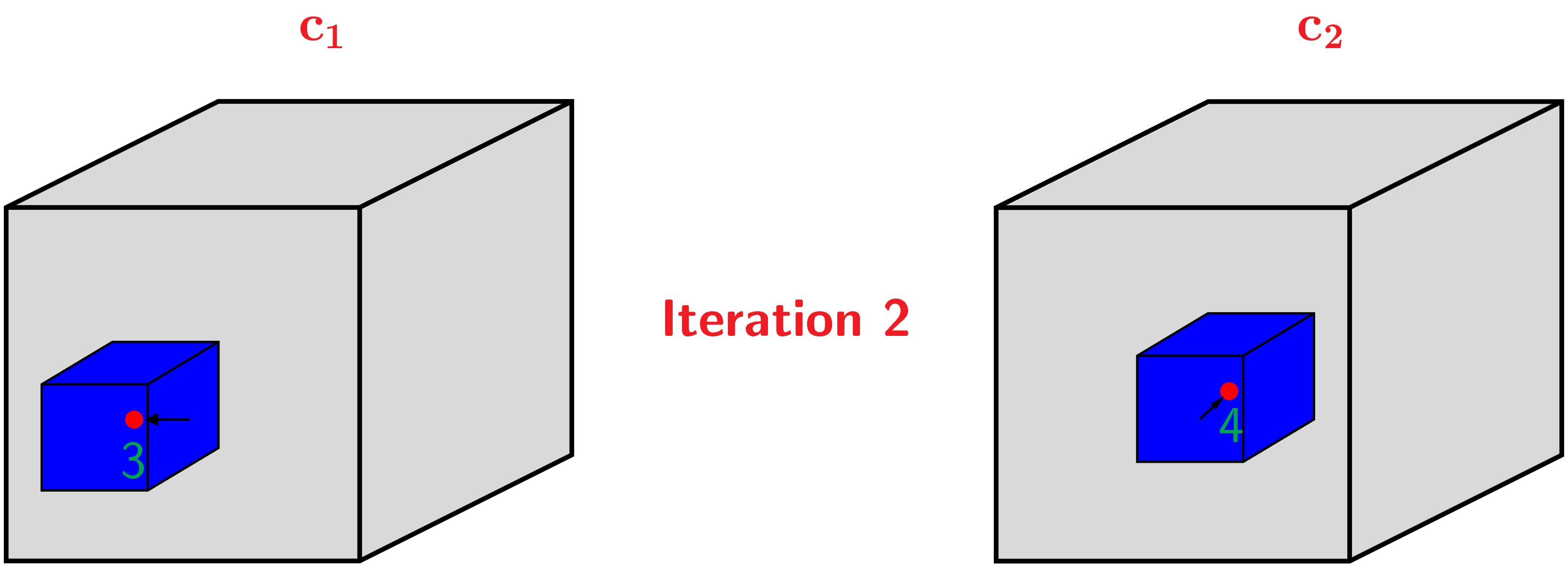


⇒ 1 and 2 are centers of the conditional search spaces.

⇒ Hypothesis $\mathbf{c_2}$ is fixed. Optimize hypothesis $\mathbf{c_1}$ by full search within its conditional search space (3).

⇒ Hypothesis $\mathbf{c_1}$ is fixed. Optimize hypothesis $\mathbf{c_2}$ by full search within its conditional search space (4).

Hypothesis Selection Algorithm III



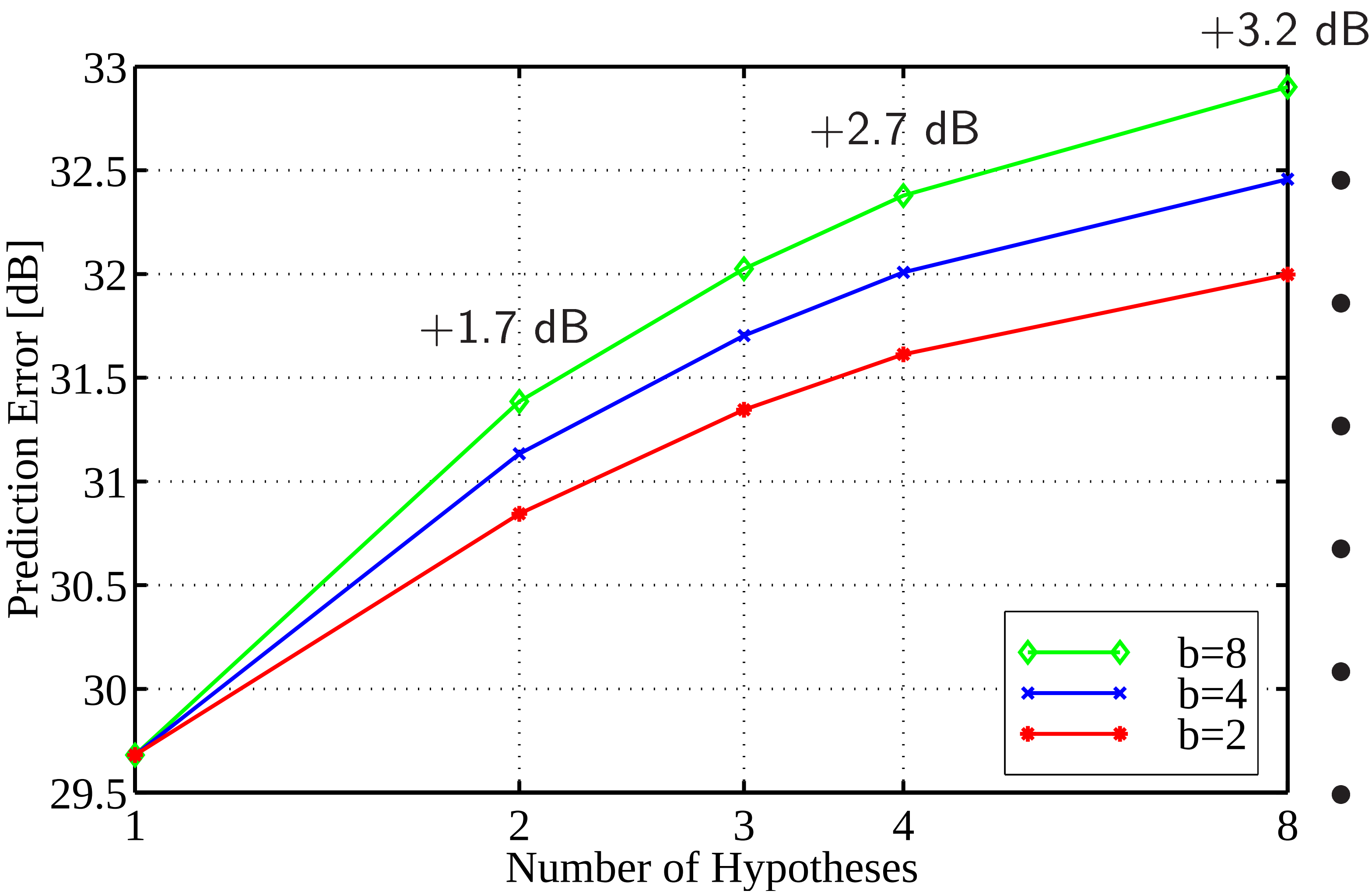
Iteration 2

⇒ 3 and 4 are centers of the conditional search spaces.

⇒ ...

Continue until convergence.

Hypothesis Selection Algorithm IV



Foreman

- QCIF
- 7.5 fps
- 10 s
- integer-pel
- 16×16 blocks
- $h_\nu = \frac{1}{n}$

Trade-off between complexity and prediction gain

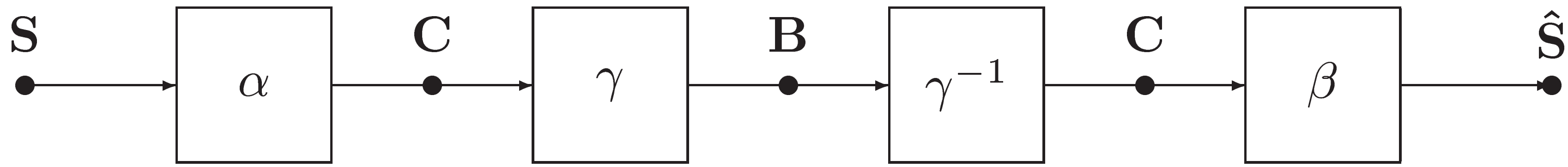
Rate-Constrained Multi-Hypothesis MCP

$\Rightarrow$ Multi-hypothesis MCP quantizes the original blocks and generates a multi-hypothesis code.

$\Rightarrow$ Improved prediction performance and higher data rate due to more than one hypothesis per block

$\hookrightarrow$ **Rate-constrained vector quantization for modeling multi-hypothesis MCP**

Predictor Model



α : Multi-hypothesis search
β : Weighted superposition
γ : Entropy code

The optimal predictor $\{\alpha^*, \beta^*, \gamma^*\}$ minimizes the average rate-distortion measure

$$J(\alpha, \beta, \gamma, \lambda, \mathbf{S}) = E\left\{ \|\mathbf{S} - \beta \circ \alpha(\mathbf{S})\|_2^2 + \lambda |\gamma \circ \alpha(\mathbf{S})| \right\}$$

for given distribution of the original blocks $\mathbf{S}_c$ and constant Lagrange multiplier λ_c.

$$\min_{\alpha,\beta,\gamma} J(\alpha, \beta, \gamma, \lambda_c, \mathbf{S}_c).$$

Iterative Design Algorithm

1: Given: Entropy code γ and predictor coefficients h

$$\min_{\mathbf{c}} \left\{ \|\mathbf{s} - \mathbf{c}h\|_2^2 + \lambda |\gamma(\mathbf{c})| \right\}$$

Optimal multi-hypothesis $\mathbf{c}$ for each original block $\mathbf{s}$

2: Given: New distribution of multi-hypotheses $\mathbf{C}$ from Step 1

$$\min_{\gamma} E\left\{ |\gamma(\mathbf{C})| \right\}$$

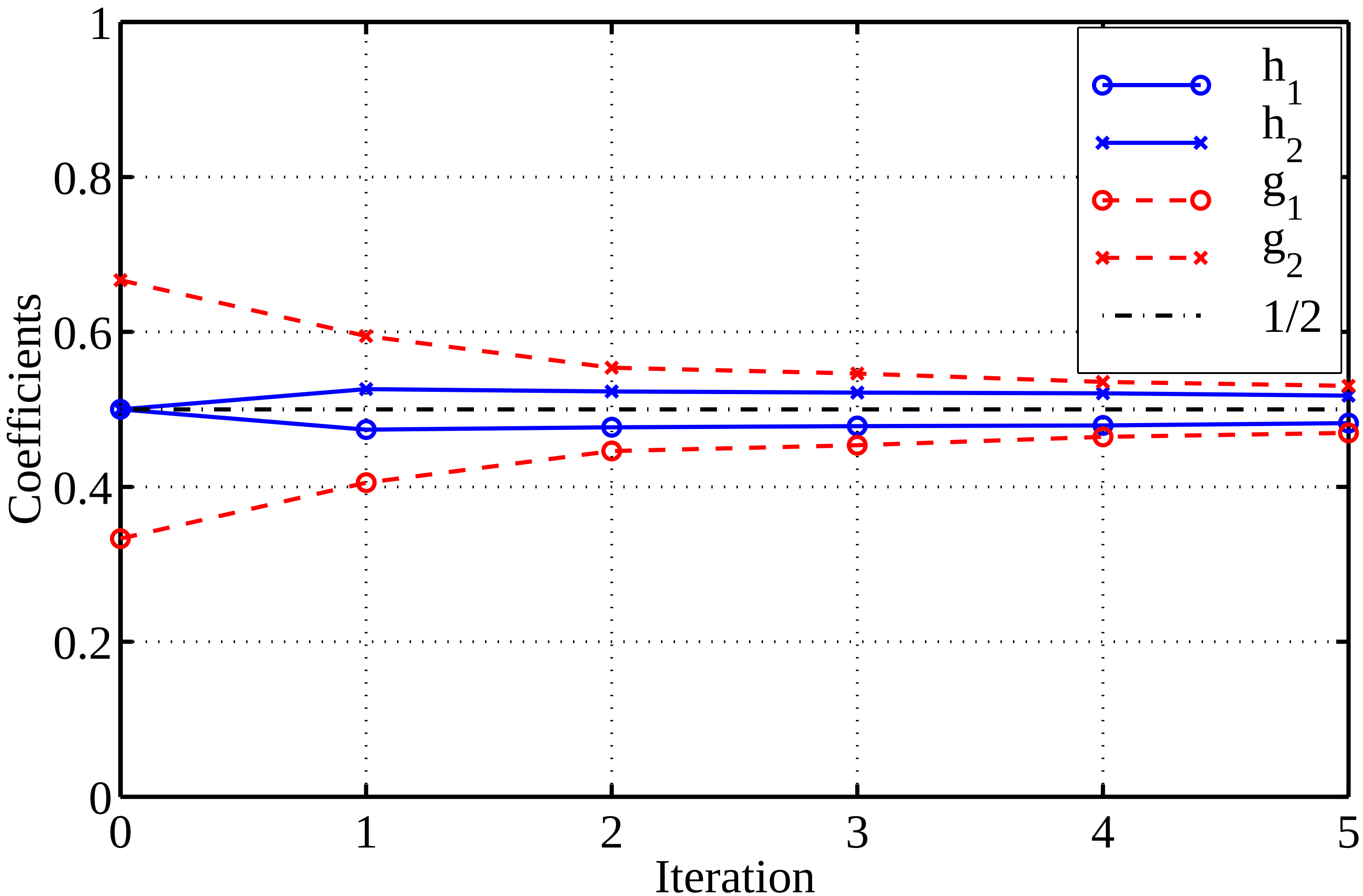
Optimal entropy code γ

3: Given: Multi-hypotheses $\mathbf{C}$ from Step 1

$$\min_{h} E\left\{ \|\mathbf{S} - \mathbf{C}h\|_2^2 \right\}$$

Optimal predictor coefficients h

Optimal Predictor Coefficients

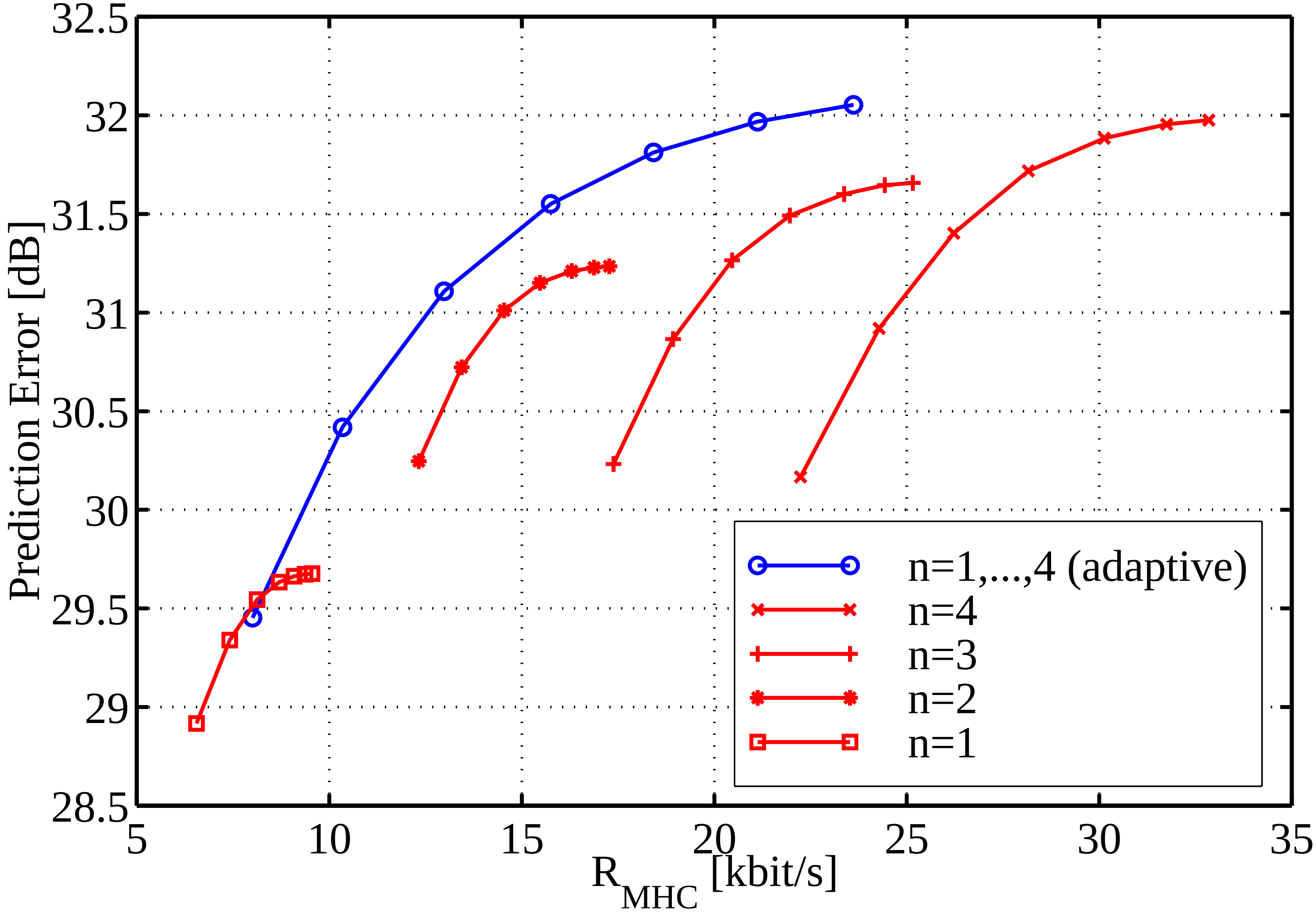


18 Sequences

- QCIF
- 7.5 fps
- 10 s
- integer-pel
- 16×16 blocks

For our parameters, the optimum predictor coefficients are approximately $\frac{1}{n}$ for n linear combined hypotheses.

Optimal Number of Hypotheses



Foreman

- QCIF
- 7.5 fps
- 10 s
- integer-pel
- 16×16 blocks
- optimal h_ν
- $b = 4$

Dependent on the rate constraint,
each block has its individual number of hypotheses.

Conclusions

$\Rightarrow$ Multi-hypothesis prediction increases prediction gain.

$\Rightarrow$ The hypothesis selection algorithm reduces the complexity of the underlying joint optimization problem to a feasible size.

$\Rightarrow$ We observed that the optimum predictor coefficients are approximately $\frac{1}{n}$ for n linear combined hypotheses.

$\Rightarrow$ Dependent on the rate constraint, each block has its individual number of hypotheses.