Fixed-finite delay decoding of i.i.d. sequences

Aditya Mahajan McGill University

Information Theory and Applications (ITA) Workshop

Motivation

Block Markov coding schemes

Used to derive achievable schemes for multi-user info theory

- ► MAC with feedback
- **▶** Broadcast with feedback
- > Relay

Share common features

- ► i.i.d. messages at each block
- decoding done with a fixed (block) delay

Motivation

Proof techniques to derive structural results in teams

Usual way to prove structural properties:

- Person-by-person optimality
- ► Coordinator with common information

Both proceed by **backward induction**. Are there situations where backward induction does not work and one has to use a **forward induction** argument?

Motivation

Proof techniques to derive structural results in teams

Our proof technique

- ► Genie-aided nodes that know additional information.
- Forward induction to discard irrelevant variables

What is the optimal structure (at block level) of block Markov coding schemes?

A new proof technique to prove

structural results in teams.

Outline

- Point-to-point communication
 - ➤ Source coding
 - ► Channel coding
 - Channel coding with feedback
- Two-transmitters one-receiver setup
 - **>** ...
- One-transmitter two-receivers
 - **>** ...

Point-to-point communication

$$S_t$$
 Encoder X_t Decoder \hat{S}_t

i.i.d. source
$$\{S_1, S_2, ...\}$$

Sequential encoder
$$X_t = f_t(S_{1:t}, X_{1:t-1})$$

Sequential decoder
$$\hat{S}_t = g_t(X_{1:t})$$

Fixed-finite delay
$$\rho_t(S_{t-d}, \hat{S}_t)$$

Objective: Choose $f = (f_1, ..., f_T)$ and $g = (g_1, ..., g_T)$ to minimize

$$J(f,g) = \mathbb{E}\left[\sum_{t=d+1}^{T} \rho_t(S_{t-d+1}, \hat{S}_t)\right]$$

- 9 Literature Overview (delay = 0)
 - ightharpoonup i.i.d. source, delay = 0 (Ericson '79)

$$X_t = f_t(S_t)$$

► Markov source, delay = 0 (Witsenhausen '79, Walrand-Varaiya '82)

$$X_t = f_t(S_t, M_{t-1})$$
 and $X_t = f_t(S_t, \mathbb{P}(S_t \mid X_{1:t-1}))$

- Literature Overview (delay > 0)
 - ► Markov source, delay > 0 (Witsenhausen '79)

$$X_t = f_t(S_{t-d:t}, M_{t-1})$$

► i.i.d. source, delay > 0 (Asnani Wiessman '11)

$$X_t = f_t(S_{t-d:t}, \mathbb{P}(S_{t-d:t} \mid X_{1:t-1}))$$

- Literature Overview (delay > 0)
 - ► Markov source, delay > 0 (Witsenhausen '79)

$$X_t = f_t(S_{t-d:t}, M_{t-1})$$

➤ i.i.d. source, delay > 0 (Asnani Wiessman '11)

$$X_t = f_t(S_{t-d:t}, \mathbb{P}(S_{t-d:t} \mid X_{1:t-1}))$$

Our result

$$X_t = f_t(S_{t-d:t}, X_{t-d:t-1})$$
 and $\hat{S}_t = g_t(X_{t-d:t})$

Markov decision processes

$$\begin{aligned} X_{t+1} &= f_t(X_t, U_t, W_t) \quad \text{and} \quad U_t &= g_t(X_{1:t}, U_{1:t-1}) \\ &\min_g \mathbb{E}^g \left[\sum_{t=1}^T c_t(X_t, U_t) \right] \end{aligned}$$

Markov decision processes

$$\begin{aligned} X_{t+1} &= f_t(X_t, U_t, W_t) \quad \text{and} \quad U_t &= g_t(X_{1:t}, U_{1:t-1}) \\ \min_g \mathbb{E}^g \left[\sum_{t=1}^T c_t(X_t, U_t) \right] \end{aligned}$$

Usual proof

Markov decision processes

$$X_{t+1} = f_t(X_t, U_t, W_t)$$
 and $U_t = g_t(X_{1:t}, U_{1:t-1})$
 $\min_{g} \mathbb{E}^g \left[\sum_{t=1}^{T} c_t(X_t, U_t) \right]$

Usual proof

Sequentially show that

$$U_T = g_T(X_T)$$

Markov decision processes

$$X_{t+1} = f_t(X_t, U_t, W_t)$$
 and $U_t = g_t(X_{1:t}, U_{1:t-1})$
 $\min_{g} \mathbb{E}^g \left[\sum_{t=1}^{T} c_t(X_t, U_t) \right]$

Weight and the second of th

Sequentially show that

$$U_T = g_T(X_T)$$

 $U_{T-1} = g_{T-1}(X_{T-1})$

Markov decision processes

$$X_{t+1} = f_t(X_t, U_t, W_t)$$
 and $U_t = g_t(X_{1:t}, U_{1:t-1})$

$$\min_{g} \mathbb{E}^g \left[\sum_{t=1}^{T} c_t(X_t, U_t) \right]$$

Usual proof

Sequentially show that

$$U_T = g_T(X_T)$$

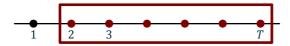
$$U_{T-1} = g_{T-1}(X_{T-1})$$

$$\cdots = \cdots$$

$$U_1 = g_1(X_1)$$

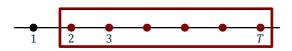
An alternative proof idea

At time 2, consider a **coordinator** for all controllers from 2 up to T.



An alternative proof idea

At time 2, consider a **coordinator** for all controllers from 2 up to *T*.



Common info
$$(X_1, U_1, X_2)$$

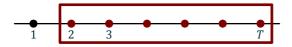
Control action
$$\gamma^{(2)} = (\gamma_2^{(2)}, \gamma_3^{(2)}, ..., \gamma_T^{(2)}) = h^{(2)}(X_1, U_1, X_2)$$

where
$$\gamma_t^{(2)}(\cdot) = g_t(X_{1:2}, U_1, \cdot) : X_{3:t} \mapsto U_t$$

Cost at coordinator
$$\tilde{c}(X_2, \gamma^{(2)})$$

An alternative proof idea

At time 2, consider a **coordinator** for all controllers from 2 up to T.

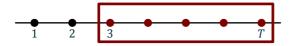


Without loss of optimality $\gamma^{(2)} = h^{(2)}(X_2)$, \Rightarrow

$$U_t = g_t(X_{2:t}, U_{2:t-1}), \quad \forall t > 2$$

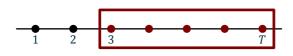
An alternative proof idea

Repeat the argument for t = 3



An alternative proof idea

Repeat the argument for t = 3



$$(X_2, U_2, X_3)$$

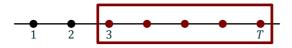
$$\gamma^{(3)} = (\gamma_3^{(3)}, \gamma_4^{(3)}, ..., \gamma_T^{(3)}) = h^{(3)}(X_1, U_1, X_2)$$

where
$$\gamma_t^{(3)}(\cdot) = g_t(X_{2:3}, U_2, \cdot) : X_{3:t}, U_{3:t-1} \mapsto U_3$$

Cost at coordinator
$$\tilde{c}(X_3, \gamma^{(3)})$$

An alternative proof idea

Repeat the argument for t = 3



Without loss of optimality $\gamma^{(3)} = h^{(3)}(X_3)$, \Rightarrow

$$U_t = g_t(X_{3:t}, U_{3:t-1}), \quad \forall t > 3$$

An alternative proof idea

Proceeding this way,

$$U_t = g_t(X_t), \quad \forall t$$

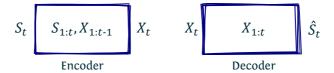
An alternative proof idea

Proceeding this way,

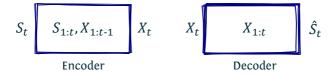
$$U_t = g_t(X_t), \quad \forall t$$

Use this **forward induction** argument to prove the structural result for the source coding setup

Information structure of the system



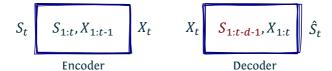
Information structure of the system



Genie aided decoder

$$S_t$$
 $S_{1:t}, X_{1:t-1}$ X_t X_t $S_{1:t-d-1}, X_{1:t}$ \hat{S}_t Encoder Decoder

9 Coordinator for [d + 2, T]



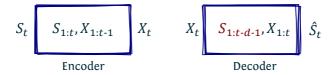
9 Coordinator for [d + 2, T]



- ightharpoonup Common info $(S_1, X_{1:d+1})$
- \triangleright Control action: appropriate partial functions $\gamma^{(d+2)}$
- ► Cost at coordinator (depends on $\mathbb{P}(S_{2:T}, \hat{S}_{d+2:T})$)

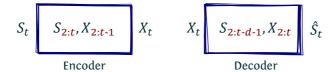
$$\tilde{c}(X_{2:d+2},\gamma^{(d+2)})$$

 $\$ Coordinator for [d+2,T]



Without loss of optimality, $\gamma^{(d+2)} = h^{(d+2)}(X_{2:d+2})$. All nodes in the coordinator may discard (S_1, X_1) .

9 Coordinator for [d + 2, T]

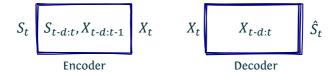


9 Coordinator for [d + 3, T]

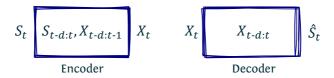
$$S_t$$
 $S_{3:t}, X_{3:t-1}$ X_t X_t $S_{3:t-d-1}, X_{3:t}$ \hat{S}_t

Encoder Decoder

© Coordinator for T



© Coordinator for *T*



The decoder does not use the additional information $S_{1:t-d-1}$.

Channel coding model

$$S_t$$
 Encoder X_t Channel Y_t Decoder \hat{S}_t

i.i.d. source

$$\{S_1, S_2, ...\}$$

Sequential encoder

$$X_t = f_t(S_{1:t}, X_{1:t-1})$$

Sequential decoder

$$\hat{S}_t = g_t(Y_{1:t})$$

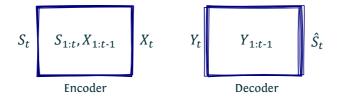
Fixed-finite delay

$$\rho_t(S_{t-\mathbf{d}}, \hat{S}_t)$$

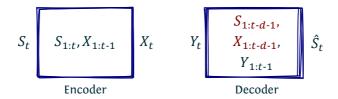
Objective: Choose $f = (f_1, ..., f_T)$ and $g = (g_1, ..., g_T)$ to minimize

$$J(f,g) = \mathbb{E}\left[\sum_{t=d+1}^{T} \rho_t(S_{t-d+1}, \hat{S}_t)\right]$$

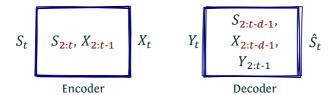
Information structure of the system



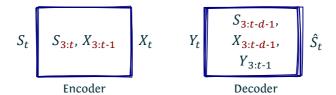
© Genie aided decoder



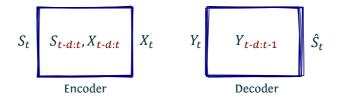
9 Coordinator for [d + 2, T]



© Coordinator for [d + 3, T]



\odot Coordinator for T



Channel coding with feedback

$$S_t$$
 Encoder Channel Y_t Decoder \hat{S}_t

i.i.d. source
$$\{S_1, S_2, ...\}$$

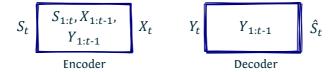
Sequential encoder
$$X_t = f_t(S_{1:t}, X_{1:t-1}, Y_{1:t-1})$$

Sequential decoder
$$\hat{S}_t = g_t(Y_{1:t})$$

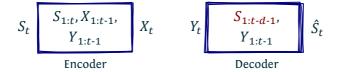
Fixed-finite delay
$$\rho_t(S_{t-d}, \hat{S}_t)$$

$$\min J(f,g) = \min \mathbb{E}\left[\sum_{t=d+1}^{T} \rho_t(S_{t-d+1}, \hat{S}_t)\right]$$

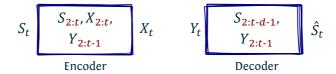
Information structure of the system



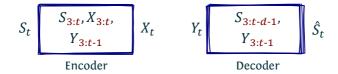
Genie aided decoder



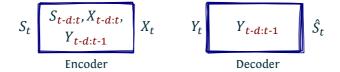
9 Coordinator for [d + 2, T]



© Coordinator for [d + 3, T]



\odot Coordinator for T



Fix decoder, consider optimal encoder

$$S_t$$
 $S_{t-d:t}, Y_{t-d:t-1}$ X_t Y_t $Y_{t-d:t-1}$ \hat{S}_t Encoder Decoder

Given channel outputs and corresponding source outputs, channel inputs are irrelevant.

Summary of results for point-to-point setup

Source coding

$$X_t = f_t(S_{t-d:t}, X_{t-d:t-1})$$
 and $\hat{S}_t = g_t(X_{t-d:t})$

© Channel coding

$$X_t = f_t(S_{t-d:t}, X_{t-d:t-1})$$
 and $\hat{S}_t = g_t(Y_{t-d:t})$

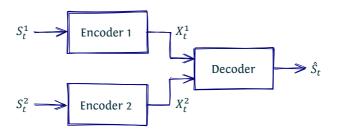
© Channel coding with feedback

$$X_t = f_t(S_{t-d:t}, Y_{t-d:t-1})$$
 and $\hat{S}_t = g_t(Y_{t-d:t})$

Multi-terminal communication

Two transmitters, one receiver

Distributed source coding



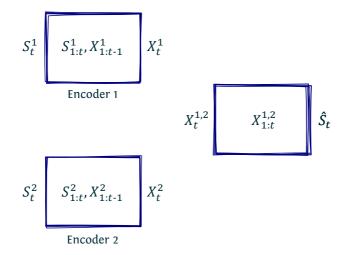
i.i.d. source
$$\{(S_1^1, S_1^2), (S_2^1, S_2^2), ...\}$$

Sequential encoder
$$X_t^k = f_t(S_{1:t}^k, X_{1:t-1}^k)$$

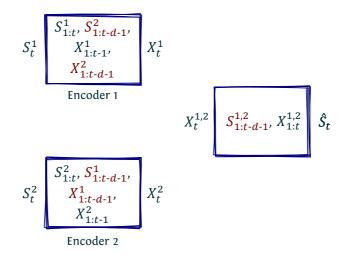
Sequential decoder
$$\hat{S}_t = g_t(X_{1:t}^1, X_{1:t}^2)$$

Fixed-finite delay
$$\rho_t(S^1_{t-d}, S^2_{t-d}, \hat{S}_t)$$

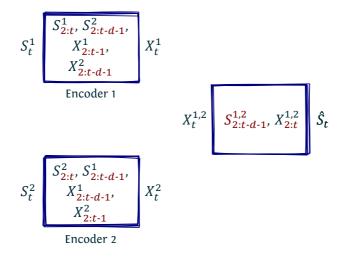
Original information structure



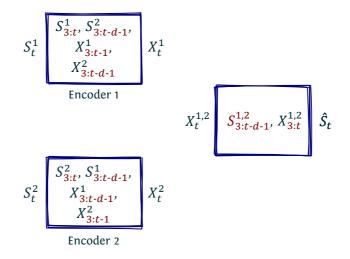
Genie aided nodes



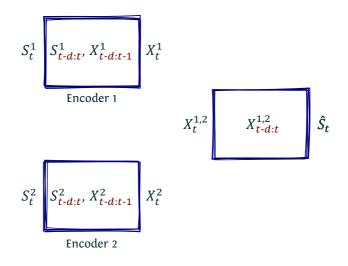
 \odot Coordinator for [d+2,T]



© Coordinator for [d + 3, T]



© Coordinator for T



Summary of results for 2-Tx 1-Rx

Multi-terminal source coding

$$X_t^k = f_t^k(S_{t-d:t}^k, X_{t-d:t-1}^k)$$
 and $\hat{S}_t = g_t(X_{t-d:t}^{1,2})$

Multiple access channel (MAC)

$$X_t^k = f_t^k(S_{t-d:t}^k, X_{t-d:t-1}^k)$$
 and $\hat{S}_t = g_t(Y_{t-d:t})$

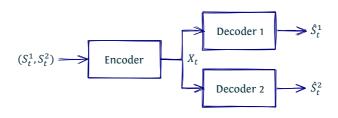
MAC with with feedback

$$X_t^k = f_t^k(S_{t-d:t}^k, X_{t-d:t-1}^k, Y_{t-d:t-1})$$
 and $\hat{S}_t = g_t(Y_{t-d:t})$

Multi-terminal communication

One transmitter, two receivers

Distributed reconstruction source coding



i.i.d. source
$$\{(S_1^1, S_1^2), (S_2^1, S_2^2), ...\}$$

Sequential encoder
$$X_t = f_t(S_{1:t}, X_{1:t-1})$$

Sequential decoder
$$\hat{S}_t^k = g_t(X_{1:t})$$

Fixed-finite delay
$$\rho_t(S^1_{t-d}, S^2_{t-d}, \hat{S}^1_t, \hat{S}^2_t)$$

Summary of results for 1-Tx 2-Rx

Distributed reconstruction

$$X_t = f_t(S_{t-d:t}^{1,2}, X_{t-d:t-1})$$
 and $\hat{S}_t^k = g_t^k(X_{t-d:t})$

Broadcast channel

$$X_t = f_t(S_{t-d:t}^{1,2}, X_{t-d:t-1})$$
 and $\hat{S}_t^k = g_t^k(Y_{t-d:t}^k)$

Broadcast channel with feedback

$$X_t = f_t(S_{t-d:t}^{1,2}, Y_{t-d:t-1})$$
 and $\hat{S}_t^k = g_t^k(Y_{t-d:t}^k)$

Concluding remarks

- Optimal structure for fixed-finite delay reconstruction of i.i.d. sequences
 - ➤ Might be useful for block Markov coding schemes.
- A (new?) proof technique to prove structural results
 - ► Genie-aided nodes with additional variables
 - ► Forward induction argument to remove irrelevant variables

Concluding remarks

Openation Dynamic programming decomposition

► All nodes have fixed memory. So we can use the approach of Sandell '74, M '08.

info state = $\mathbb{P}(Memory of all nodes at t)$

Time-varying optimal control laws!

► "State" observed after a delay. So we can also use the approach of Aicardi *et al.* '87, Nayyar M Teneketzis '12

info state = (local memory, (partially evaluated functions)

Time-invariant optimal control laws!

Thank you