Proof (Part ii): Since $f(t)$ is a nondecreasing function of $t$, (1) and (2) yield

$$
\begin{align*}
E\left[d_{n}(X, \tilde{X})\right] & \geq \frac{f(n)}{n}\left(E \sum_{t=0}^{n-1}\left(1-\delta\left(X_{t}, \tilde{X}_{t}\right)\right)\right) \\
& \geq \frac{f(n)}{n} E[1-\delta(X, \tilde{X})] \\
& =P_{e} f(n) / n . \tag{5}
\end{align*}
$$

For equally probable source vectors, Theorem 1-ii lowerbounds $P_{e}$ and thus

$$
\begin{equation*}
E\left[d_{n}(X, \tilde{X})\right] \geq \frac{f(n)}{n} \exp \left[-n\left[E_{s p}\left(R-o_{1}(n)\right)+o_{2}(n)\right]\right] . \tag{6}
\end{equation*}
$$

Part ii easily follows from (6).
$\operatorname{Proof}($ Part $i)$ : Since $[1-\delta(x, \tilde{x})]^{2}=[1-\delta(x, \tilde{x})]$, applying the Schwartz inequality to (1) yields

$$
\begin{align*}
& E\left[d_{n}(X, \tilde{X})\right] \\
& <\left(n^{-1} \sum_{t=0}^{n-1}[f(t+n)]^{2}\right)^{1 / 2}\left(E\left[n^{-1} \sum_{t=0}^{n-1}\left(1-\delta\left(X_{t}, \tilde{X}_{t}\right)\right)\right]\right)^{1 / 2} . \tag{7}
\end{align*}
$$

Since $\left[n^{-1} \sum_{t=0}^{n-1}\left(1-\delta\left(x_{t}, \tilde{x}_{t}\right)\right)\right] \leq[1-\delta(x, \tilde{x})]$, Theorem $1-i$ and (7) yields

$$
\begin{equation*}
E\left[d_{n}(X, \tilde{X})\right] \leq\left(n^{-1} \sum_{t=0}^{n-1}[f(t+n)]^{2}\right)^{1 / 2}\left(\exp \left[-n E_{r}(R)\right]\right)^{1 / 2} \tag{8}
\end{equation*}
$$

Part i easily follows from (8) and Theorem 1-iii.
Thus, $f(t)$ can grow exponentially (but not too fast) and still have $E\left[d_{n}(\boldsymbol{X}, \tilde{\boldsymbol{X}})\right] \rightarrow 0$. In the following theorem it is interesting to see that a similar property does not hold for $C<H(X)$.

Theorem 3: Assume that the source letters are independent and identically distributed and that

$$
\begin{equation*}
d_{n}(x, \tilde{x}) \geq n^{-1} \sum_{t=0}^{n-1} f(t) p\left(x_{t}, \tilde{x}_{t}\right) \tag{9}
\end{equation*}
$$

where $\rho(x, \tilde{x})$ is nonnegative and $f(t)$ is a nondecreasing function of $t$ such that $\lim _{t \rightarrow \infty} f(t)=\infty$. Let $R_{\rho}(D)$ be the rate distortion function with respect to $\rho(x, \tilde{x})$. If the channel capacity $C<$ $R_{\rho}(0) \triangleq \lim _{D \rightarrow \infty} R_{\rho}(D)$, then for every sequence of block length $n$ codes

$$
\begin{equation*}
\lim _{n \rightarrow \infty} E\left[d_{n}(X, \tilde{X})\right]=\infty \tag{10}
\end{equation*}
$$

Note: Usually $R_{\rho}(0)=H(X)$. Thus this theorem shows that for any channel of capacity $C<H(X)$, infinite block length codes perform very poorly no matter how slowly $f(t) \rightarrow \infty$.

## Proof: Let

$$
\begin{equation*}
R_{n}(D)=\min _{\left[D_{t}: n^{-1} \sum_{t=0}^{n-1} D_{t}=D\right]}\left[n^{-1} \sum_{t=0}^{n-1} R^{t}\left(D_{t}\right)\right] \tag{11}
\end{equation*}
$$

where $R^{t}\left(D_{t}\right)=R_{\rho}\left(D_{t} / f(t)\right) . \mathrm{R}_{n}(D)$ may be thought of as the rate-distortion function for the product of $n$ sources with sum distortion measure where the $t$ th source has distortion measure. For equally probable source vectors, Theorem 1-ii lower$f(t) p(x, x)$. (See Berger [4, sect. 2.8].) Therefore, if $C<R /(D)$, then $E[d /(X, \bar{X})]>D$, for all block length $n$ codes. Since $f(t)$ is
nondecreasing and $R!(D)$ is convex upward and nonincreasing, it follows that for any $N$

$$
\begin{align*}
R_{n}(D) & \geq \min _{\left\{D_{t}: n^{-1} \Sigma_{t=0}^{n-1} D_{t}=D\right]}\left[n^{-1} \sum_{t=N}^{n-1} R_{\rho}\left(D_{t} / f(N)\right)\right] \\
& =\frac{n-N}{n} R_{\rho}\left[\left(\frac{n}{n-N}\right)\left(\frac{D}{f(N)}\right)\right] . \tag{12}
\end{align*}
$$

Therefore, $\lim _{n \rightarrow \infty} R_{n}(D) \geq R_{\rho}(D / f(N))$. Since $N$ is an arbitrarily large number and $f(t) \rightarrow \infty$, we have $\lim _{n \rightarrow \infty} R_{n}(D)=$ $R_{\rho}(0)$. The theorem is proven since for any $D>0$ and sufficiently large $n$, we have $R_{n}(D)>C$.

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## A Simple Converse for Broadcast Channels with Additive White Gaussian Noise

## PATRICK P. BERGMANS

Abstract-Sets of achievable rates for the additive white Gaussian noise broadcast channel have been found by Cover [1] for channels with two outputs and generalized by Bergmans [2] to channels with any number of outputs. In this correspondence, we establish a simple converse showing the optimality of these sets of achievable rates. The proof is made simple by use of special properties of the Gaussian channel.

The set of achievable rates for discrete-time additive white Gaussian noise (AWGN) broadcast channels with noise powers $N_{1}<N_{2} \cdots N_{N}$ in the different links and average input power $S$ is given by [1], [2]

$$
\begin{equation*}
R_{i} \leq \frac{1}{2} \ln \left(1+\frac{\alpha_{i} S}{N_{i}+\sum_{j<i} \alpha_{j} S}\right), \quad i \doteq 1, \cdots, N \tag{1}
\end{equation*}
$$

with $\alpha_{i} \geq 0, \sum \alpha_{i}=1$.
In this correspondence, we shall use the equivalent notation

$$
\begin{equation*}
R_{i} \leq g\left(N_{i}+\beta_{i} S\right)-g\left(N_{i}+\beta_{t-1} S\right), \quad i=1, \cdots, N \tag{2}
\end{equation*}
$$

with

$$
\begin{equation*}
g(S) \triangleq \frac{1}{2} \ln (2 \pi e S) \tag{3}
\end{equation*}
$$

and

$$
\begin{equation*}
0=\beta_{0} \leq \beta_{1} \leq \beta_{2} \leq \cdots \leq \beta_{N}=1 \tag{4}
\end{equation*}
$$

We shall need the following lemmas.
Lemma I: Let $X$ be a random $n$-tuple such that $X \in R^{n}$, $H(\boldsymbol{X}) \geq n v$, and let $\boldsymbol{Y}=\boldsymbol{X}+\boldsymbol{Z}$ where $\boldsymbol{Z}$ is a Gaussian noise vector independent of $\boldsymbol{X}$ with independent zero-mean components of yariance $N$. Then

$$
\begin{equation*}
H(\boldsymbol{Y}) \geq n g\left(N+g^{-1}(v)\right) \tag{5}
\end{equation*}
$$

[^0]

Fig. 1.

Lemma II: Consider the ensemble $(X, Y, W)$, such that $X \in R^{n}$, $W \in I_{1} \times I_{2} \times \cdots \times I_{k}$ (a product of index sets), $H(X \mid W) \geq$ $n v$, and let $\boldsymbol{Y}=\boldsymbol{X}+\boldsymbol{Z}$, with $\boldsymbol{Z}$ as in Lemma $I$. Then

$$
\begin{equation*}
H(\boldsymbol{Y} \mid W) \geq n g\left(N+g^{-1}(v)\right) \tag{6}
\end{equation*}
$$

Lemma $I$ is a straightforward consequence of an inequality of Shannon on the entropy power of the sum of two ensembles [3, p. 636], [4]. It is the counterpart for the Gaussian case of the results obtained by Wyner and Ziv for the binary case [5]. Lemma II is just the conditional version of Lemma $I$, and can be established easily using Lemma I, the convexity of $g\left(N+g^{-1}(v)\right)$ in $v$ and Jensen's inequality.

We now state the converse to the coding theorem.
Theorem: No point ( $R_{1} \cdots R_{N}$ ) such that

$$
\begin{array}{ll}
R_{i} \geq g\left(N_{i}+\beta_{i} S\right)-g\left(N_{i}+\beta_{i-1} S\right), & i=1, \cdots, N \\
R_{j}=g\left(N_{j}+\beta_{j} S\right)-g\left(N_{j}+B_{j-1} S\right)+\delta, & \text { some } j, \delta>0
\end{array}
$$

is achievable, where the $\beta_{j}$ are as in (4).
Proof (by Contradiction): We suppose that the rates of (7) are achievable. We refer to Fig. 1 for the meaning of the various quantities. The outputs of the sources are independent and equiprobable.

If the rates of (7) are achievable, the probability of decoding error for each receiver can be upper bounded by an arbitrarily small $\lambda$ (for sufficiently large $n$ )

$$
\begin{equation*}
\operatorname{Pr}\left[\hat{W}_{i} \neq W_{i} \mid \boldsymbol{Y}_{i}\right]<\lambda, \quad i=1, \cdots, N \tag{8}
\end{equation*}
$$

This implies (Fano's inequality)

$$
\begin{equation*}
H\left(W_{i} \mid \boldsymbol{Y}_{i}\right) \leq h(\lambda)+\lambda \log \left(M_{i}-1\right), \quad i=1, \cdots, N . \tag{9}
\end{equation*}
$$

Using standard information-thcorctic arguments and the independence of the $W_{i}$, we find, from (9)

$$
\begin{align*}
\log M_{i} & \leq I\left(\boldsymbol{Y}_{i} ; W_{i} \mid W_{i+1} \cdots W_{N}\right)+\varepsilon_{i}(\lambda) \\
& =H\left(\boldsymbol{Y}_{i} \mid W_{i+1} \cdots W_{N}\right)-H\left(\boldsymbol{Y} \mid W_{i} \cdots W_{N}\right)+\varepsilon_{i}(\lambda) \tag{10}
\end{align*}
$$

where $\varepsilon_{i}(\lambda) \rightarrow 0$ as $\lambda \rightarrow 0$.
From (7)

$$
\begin{equation*}
\log M_{i} \geq n g\left(N_{i}+\beta_{i} S\right)-n g\left(N_{i}+\beta_{i-1} S\right) \tag{11}
\end{equation*}
$$

Next, using Lemma II, (10) (an upper bound for $\log M_{i}$ ) and (11) (a lower bound for $\log M_{i}$ ), we show in the Appendix

$$
\begin{equation*}
H\left(Y_{i} \mid W_{i+1} \cdots W_{N}\right) \geq n g\left(N_{i}+\beta_{i} S\right)-\eta_{i}(\lambda) \tag{12}
\end{equation*}
$$

where $\eta_{i}(\lambda) \rightarrow 0$ as $\lambda \rightarrow 0$, and where $n \delta$ should be added to the right side of (12), for $i \geq j$ (where $j$ was defined in the statement of the theorem). It follows from (12), with $i=N \geq j$, that

$$
\begin{equation*}
H\left(Y_{N}\right) \geq n g\left(N_{N}+S\right)-\eta_{N}(\lambda)+n \delta . \tag{13}
\end{equation*}
$$

Since $\lambda$, and hence $\eta_{N}(\lambda)$, can be made arbitrarily small, we may conclude that, for sufficiently large $n, H\left(Y_{N}\right) \geq n g\left(N_{N}+S\right)+n \delta$. This, however, is impossible, since $\operatorname{var}\left(Y_{N}\right) \leq N_{N}+S$ and, therefore, $H\left(Y_{N}\right) \leq n g\left(N_{N}+S\right)$. The desired contradiction has been obtained, so the theorem is proved.

## Appendix

## Proof of Equation (12)

Letting $i=1$ in (10) and (11), we find

$$
\begin{aligned}
H\left(Y_{1} \mid W_{2} \cdots W_{N}\right)-H\left(Y_{1} \mid W_{1} \cdots\right. & \left.W_{N}\right)+\varepsilon_{1}(\lambda) \\
& \geq n g\left(N_{1}+\beta_{1} S\right)-n g\left(N_{1}\right)
\end{aligned}
$$

or

$$
\begin{equation*}
H\left(Y_{1} \mid W_{2} \cdots W_{N}\right) \geq n g\left(N_{1}+\beta_{1} S\right)-\eta_{1}(\lambda) \tag{14}
\end{equation*}
$$

since

$$
H\left(Y_{1} \mid W_{1} \cdots W_{N}\right)=H\left(Y_{1} \mid X\right)=n g\left(N_{1}\right)
$$

The rest of the proof is by recursion. We assume that (12) is true. Writing (10) and (11) for $i+1$, we find

$$
\begin{align*}
H\left(Y_{i+1} \mid W_{i+2} \cdots W_{N}\right) \geq & n g\left(N_{i+1}+\beta_{i+1} S\right)-n g\left(N_{i+1}+\beta_{i} S\right) \\
& +H\left(Y_{i+1} \mid W_{i+1} \cdots W_{N}\right)-\varepsilon_{i+1}(\lambda) \tag{15}
\end{align*}
$$

From (12)

$$
\begin{equation*}
H\left(Y_{i} \mid W_{i+1} \cdots W_{N}\right) \geq n\left[g\left(N_{i}+\beta_{i} S\right)-\frac{\eta_{i}(\lambda)}{n}\right] \tag{16}
\end{equation*}
$$

Since $Y_{i+1}$ is obtained by adding Gaussian noise of variance $N_{i+1}-N_{i}$ to $Y_{i}$, we have, using Lemma II

$$
\begin{align*}
H & \left(Y_{i+1} \mid W_{i+1} \cdots W_{N}\right) \\
& \geq n g\left[\left(N_{l+1}-N_{i}\right)+g^{-1}\left(g\left(N_{i}+\beta_{i} S\right)-\frac{\eta_{i}(\lambda)}{n}\right)\right] \\
& =n g\left[\left(N_{i+1}-N_{i}\right)+g^{-1} g\left(N_{i}+\beta_{i} S\right)-\frac{\zeta_{i}(\lambda)}{n}\right] \\
& =n g\left(N_{i+1}+\beta_{i} S\right)-\xi_{i}(\lambda) \tag{17}
\end{align*}
$$

where $\zeta\left({ }_{i} \lambda\right), \xi_{i}(\lambda) \rightarrow 0$ as $\lambda \rightarrow 0$. Substitution of (17) in (15) yields

$$
\begin{equation*}
H\left(Y_{i+1} \mid W_{i+2} \cdots W_{N}\right) \geq n g\left(N_{i+1}+\beta_{i+1} S\right)-\eta_{i+1}(\lambda) \tag{18}
\end{equation*}
$$

with $\eta_{i+1}(\lambda)=\varepsilon_{i+1}(\lambda)+\xi_{i}(\lambda) \rightarrow 0$ as $\lambda \rightarrow 0$. Equation (18) establishes the recursion. Finally, for $i \geq j, n \delta$ should be added to the right side of (18) because of the presence of $\delta$ in (7) for $i=j$, and, hence, of $n \delta$ in (11).

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