ADAPTIVE ITERATIVE DECISION MULTI-FEEDBACK DETECTION FOR MULTI-USER MIMO SYSTEMS

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ABSTRACT

An adaptive iterative decision multi-feedback detection algorithm with constellation constraints is proposed for multiuser multiantenna systems. An enhanced detection and interference cancellation is performed by introducing multiple constellation points as decision candidates. A complexity reduction strategy is developed to avoid redundant processing with reliable decisions along with an adaptive recursive least squares algorithm for time-varying channels. An iterative detection and decoding scheme is also considered with the proposed detection algorithm. Simulations show that the proposed technique has a complexity as low as the conventional decision feedback detector while it obtains a performance close to the maximum likelihood detector.

Index Terms— MIMO systems, decision feedback receivers, RLS algorithms, multi-user detection, iterative processing.

1. INTRODUCTION

Multi-user detection (MUD) algorithms have shown that they can be applied to 3G and next generation multi-antenna communication systems [1]. As the optimal maximum likelihood detector (MLD) has an exponential computational cost in the number of users and constellation points, cost-effective solutions such as the sphere decoder (SD) and decision feedback (DF) receivers [2, 3] are preferred as they offer an acceptable performance and complexity trade-off in spatial multiplexing multi-input multi-output (MIMO) systems. For time-varying channels, adaptive DF structures [4, 7, 6] are promising as adaptive algorithms can be used to track the channels and to avoid excessive computations when the channels are time-varying. However, the performance of DF techniques are far from the MLD.

In this paper, an adaptive decision feedback based algorithm is proposed for signal detection in multi-user MIMO (MU-MIMO) systems with time-varying channels. The proposed DF algorithm can reduce the performance gap between the optimal MLD and existing DF algorithms. The proposed DF algorithm exploits multiple constellation points and orderings to obtain several detection candidates. A reliability checking technique called constellation constraint (CC) brings improved performance to the proposed DF detector at a small additional computational cost as compared to the conventional DF. We also consider an iterative detection and decoding (IDD) scheme in which the proposed DF detector is incorporated.

This paper is organized as follows: Section 2 gives the data and system model of the MU-MIMO system; the proposed detection scheme is described in Section 3, whereas the IDD scheme is detailed in Section 4; the simulation results are shown in Section 5 and Section 6 presents the conclusions of the paper.

2. DATA AND SYSTEM MODEL

Let us consider a model of an uplink MU-MIMO system with K users. Each user is equipped with a single antenna. At the receiver side, N_R receive antennas are available for collecting the signals. Throughout this paper, the complex baseband notation is

used while vectors and matrices are written in lower-case and uppercase boldface, respectively. At each time instant [i], K users simultaneously transmit K symbols organized into a vector $\mathbf{s}[i] = [s_1[i], s_2[i], \ldots, s_K[i]]^T$, where $(\cdot)^T$ denotes the transpose operation, and whose entries are chosen from a complex C-ary constellation set $\mathcal{A} = \{a_1, a_2, \ldots, a_C\}$. The symbol vector $\mathbf{s}[i]$ is transmitted over time-varying channels and the received signal is processed by N_R antennas. The received signal is collected to form an $N_R \times 1$ vector with sufficient statistics for detection

$$\boldsymbol{r}[i] = \sum_{k=1}^{K} \boldsymbol{h}_{k}[i]\boldsymbol{s}_{k}[i] + \boldsymbol{v}[i] = \boldsymbol{H}[i]\boldsymbol{s}[i] + \boldsymbol{v}[i], \qquad (1)$$

where the $N_R \times 1$ vector v[i] represents a zero mean complex circular symmetric Gaussian noise with covariance matrix $E[v[i]v^H[i]] = \sigma_v^2 I$, σ_v^2 is the noise variance and I is the identity matrix, $E[\cdot]$ stands for the expected value and $(\cdot)^H$ denotes the Hermitian operator. The symbol vector s[i] has zero mean and a covariance matrix $E[s[i]s^H[i]] = \sigma_s^2 I$, where σ_s^2 is the signal power. Furthermore, the elements of H[i] are the time-varying complex channel gains from the n_T -th transmit antenna to the n_R -th receive antenna, which follow the Jakes' model [11]. The $N_R \times 1$ vector $h_k[i]$ includes the channel coefficients of user k such that H[i] is formed by the channel vectors of all users. As the optimal SINR-based nulling and cancellation order (NCO) [4] requires a high computational complexity, we determine the NCO by computing the norms of the column vectors corresponding to all users and we then detect them in decreasing order of their norms.

3. PROPOSED ADAPTIVE MULTI-USER DF DETECTOR

In the proposed adaptive multi-user DF detector, called AMUDFCC, the received signal r[i] is filtered by a $N_R \times 1$ forward filter $\omega_{f,k}^{I}[i]$ which acts as the nulling vectors of the V-BLAST algorithm. Then for each user stream $k = 1, \ldots, K$, the decisions are accumulated and cancelled by the (k - 1)-dimensional decision backward filter $\omega_{b,k}^{H}[i]$. Let $\hat{s}[i] = [\hat{s}_1[i], \hat{s}_2[i], \ldots, \hat{s}_K[i]]^T$ represent the detected symbol vector and $u_k[i]$ denotes the difference between the forward filter output and the backward filter output as described as

$$u_k[i] = \boldsymbol{\omega}_{f,k}^H[i]\boldsymbol{r}[i] - \boldsymbol{\omega}_{b,k}^H[i]\hat{\boldsymbol{s}}_{k-1}[i], \qquad (2)$$

where $\boldsymbol{\omega}_{b,1}^{H} = \mathbf{0}$ for the first user and the (k-1)-dimensional detected symbol vector is defined as

$$\hat{\boldsymbol{s}}_{k-1}[i] = [\hat{s}_1, \hat{s}_2, \dots, \hat{s}_{k-1}]^T.$$
 (3)

For notational convenience, the feedforward and feedback filters can be concatenated together as [4]

$$\tilde{\boldsymbol{\omega}}_{k}[i] = \begin{cases} \boldsymbol{\omega}_{f,k}[i], & k = 1\\ \left[\boldsymbol{\omega}_{f,k}^{T}[i], \boldsymbol{\omega}_{b,k}^{T}[i]\right]^{T}, & k = 2, \dots, K. \end{cases}$$
(4)

The input can also be concatenated as

$$\tilde{\boldsymbol{r}}_{k}[i] = \begin{cases} \boldsymbol{r}[i], & k = 1\\ \left[\boldsymbol{r}^{T}[i] - \hat{\boldsymbol{s}}_{k-1}^{T}[i]\right]^{T}, & k = 2, \dots, K. \end{cases}$$
(5)

Then, we can rewrite (2) as

$$u_k[i] = \tilde{\boldsymbol{\omega}}_k^H[i]\tilde{\boldsymbol{r}}_k[i].$$
(6)



Fig. 1: Block diagram of the proposed AMUDFCC detector.

As a result, the structure and the signal processing model of the proposed DF detector are depicted in Fig.1. We denote the receive filter of each user as $\tilde{\omega}_k^H[i]$ ($k = 1, \ldots, K$), and the value of each entry can be obtained by solving the standard least squares (LS) problem. The LS cost function with an exponential window is given by

$$\mathcal{J}_{k}[i] = \sum_{\tau=1}^{i} \lambda^{i-\tau} \left| \hat{s}_{k}[\tau] - \tilde{\boldsymbol{\omega}}_{k}^{H}[i] \tilde{\boldsymbol{r}}_{k}[\tau] \right|^{2}, \tag{7}$$

where $0 \ll \lambda < 1$ is the forgetting factor, the scalar $\hat{s}_k[\tau]$ denotes the detected signal in the time index τ or the known pilots where $\hat{s}_k[\tau] = s_k[\tau]$. The optimal tap weight minimizing $\mathcal{J}_k[i]$ is given by

$$\tilde{\boldsymbol{\omega}}_{k}[i] = \boldsymbol{\Phi}_{k}^{-1}[i]\boldsymbol{p}_{k}[i], \qquad (8)$$

where the time-averaged cross correlation matrix is obtained by $\Phi_k[i] = \sum_{\tau=1}^i \lambda^{i-\tau} \tilde{\boldsymbol{r}}_k[\tau] \tilde{\boldsymbol{r}}_k^H[\tau]$ and $\Phi_k[0] = \boldsymbol{0}$, the time-averaged cross correlation vector is defined by $\boldsymbol{p}_k[i] = \sum_{\tau=1}^i \lambda^{i-\tau} \tilde{\boldsymbol{r}}_k[\tau] \hat{\boldsymbol{s}}_k^*[\tau]$.

Using the recursive least squares (RLS) algorithm [9], the optimal weights in (8) can be calculated recursively as follows:

$$\boldsymbol{q}_{k}[i] = \boldsymbol{\Phi}_{k}^{-1}[i-1]\boldsymbol{r}_{k}[i], \qquad (9)$$

$$\boldsymbol{k}_{k}[i] = \frac{\lambda^{-1}\boldsymbol{q}_{k}[i]}{1 + \lambda^{-1}\boldsymbol{r}_{k}^{H}[i]\boldsymbol{q}_{k}[i]},\tag{10}$$

$$\boldsymbol{\Phi}_{k}^{-1}[i] = \lambda^{-1} \boldsymbol{\Phi}_{k}^{-1}[i-1] - \lambda^{-1} \boldsymbol{k}_{k}[i] \boldsymbol{q}_{k}^{H}[i], \qquad (11)$$

$$\tilde{\boldsymbol{\omega}}_{k}[i] = \tilde{\boldsymbol{\omega}}_{k}[i-1] + \boldsymbol{k}_{k}[i]\boldsymbol{\xi}_{k}^{*}[i], \qquad (12)$$

where

$$\xi_k[i] = \begin{cases} s_k[i] - \tilde{\boldsymbol{\omega}}_k^H[i-1]\tilde{\boldsymbol{r}}_k[i], & \text{Training Mode,} \\ \hat{s}_k[i] - \tilde{\boldsymbol{\omega}}_k^H[i-1]\tilde{\boldsymbol{r}}_k[i], & \text{Decision-directed Mode.} \end{cases}$$
(13)

As indicated in (13), this adaptive detection algorithm works in two modes. The first one is employed with the training sequence, while the second one is the decision-directed mode that is switched on after the filter weights converge. In the decision-directed mode the quality of the detected symbols has a major impact on the performance of adaptive DF algorithms. This is because the detection error of the current user may propagate throughout the detection of the following users. Moreover, in time-varying channels a poor $\xi_k[i]$ can easily damage the $\tilde{\omega}_k[i]$ in equation (12) resulting in burst errors.

3.1. Constellation Constraints

d

When the filter output $u_k[i]$ is considered unreliable, the CC scheme produces a number of selected constellation points as the candidate decisions. A selection algorithm is introduced to prevent the search space from growing exponentially, saving computational complexity by avoiding redundant processing with reliable decisions. In



Fig. 2: The constellation constraints (CC) device. The CC procedure is invoked as the soft estimates $u_k[i]$ drop into the shaded area.

the decision-directed mode, the concatenated filter output $u_k[i]$ is checked by the CC device which is illustrated in Fig.2, where a threshold $d_{\rm th}$ is defined which can be either a constant or a linear function of σ_v . The CC device finds the nearest constellation point to $u_k[i]$ according to

$$a_k[i] = \arg\min_{a_c \in \mathcal{A}} \left\{ |u_k[i] - a_c| \right\},\tag{14}$$

where a_c represents all potential constellation points. A decision is considered unreliable if at least one of the following conditions holds

$$> d_{\text{th}} \quad \text{when} \quad \begin{cases} |\text{Re}\{u_k[i]\}| \le \frac{\sigma_s}{\sqrt{2}} \\ |\text{Im}\{u_k[i]\}| \le \frac{\sigma_s}{\sqrt{2}} \end{cases} \tag{15}$$

$$\begin{aligned} \left| \operatorname{Re}\{u_{k}[i]\} \right| &< \frac{\sigma_{s}}{\sqrt{2}} - d_{\operatorname{th}} \\ \operatorname{OR} \\ \left| \operatorname{Im}\{u_{k}[i]\} \right| &< \frac{\sigma_{s}}{\sqrt{2}} - d_{\operatorname{th}} \end{aligned}$$
 when
$$\begin{cases} \left| \operatorname{Re}\{u_{k}[i]\} \right| > \frac{\sigma_{s}}{\sqrt{2}} \\ \left| \operatorname{Im}\{u_{k}[i]\} \right| > \frac{\sigma_{s}}{\sqrt{2}} \end{cases}$$
 (16)

where d denotes the distance between the estimated symbol $u_k[i]$ and its nearest constellation point $a_k[i]^{-1}$. Instead of finding the closest vector, in fact, the scalar constellation helps to reduce the cost. Since the CC device distinguishes whether the feedback signal is reliable, the detector maintains its complexity at the same level of the conventional DF structure. Once the filter output $u_k[i]$ drops into the lighted area of the constellation map, the decision is considered reliable and the quantization operation $Q(\cdot)$ is then performed

$$\hat{s}_k[i] = \mathcal{Q}(u_k[i]). \tag{17}$$

If $u_k[i]$ drops into the shadowed area, the decision is determined unreliable. The CC processing is evoked and a candidate vector is generated as $\mathcal{L} = \{c_1, c_2, \ldots, c_m, \ldots, c_M\} \subseteq \mathcal{A}$. The candidates are constrained by the constellation map and the selected vector is a selection of the M nearest constellation points to the $u_k[i]$. The size of \mathcal{L} can be either fixed or variable, which introduces a trade off between the performance and complexity.

The refined estimate is obtained by $\hat{s}_k[i] = c_{\text{opt}}$ where c_{opt} is the optimal candidate selected from \mathcal{L} . This refined decision will

¹Equation (16) defines the shadowed area inside the square obtained by connecting the four a_c ($a_c = (\pm \sigma_s/\sqrt{2}, \pm j\sigma_s/\sqrt{2})$). Equation (15) denotes the shadowed area outside the square. This concept can be further extended to multi-tier constellations, eg. 16-QAM.

produce a more accurate $\xi_k[i]$ which minimizes the mean square error (MSE). The benefits offered by the CC algorithm are based on the assumption that the optimal feedback candidate c_{opt} is correctly selected. This selection algorithm is described as follows: a set of tentative decision vectors $\boldsymbol{B}_k = \{\boldsymbol{b}_k^1, \ldots, \boldsymbol{b}_k^M, \ldots, \boldsymbol{b}_k^M\}$ is defined and the number of tentative decision vectors \boldsymbol{M} equal the number of selected constellation candidates. Each vector \boldsymbol{b}_k^m is defined as $\boldsymbol{b}_k^m[i] = [\hat{s}_1[i], \ldots, \hat{s}_{k-1}[i], c_m, \hat{b}_{k+1}[i], \ldots, \hat{b}_K[i]]$, the $K \times 1$ vector \boldsymbol{b}_k^m consists of: 1) (k-1)-dimensional detected symbol vector $\hat{s}_{k-1}[i]$ which is used in (5); 2) a candidate symbol c_m taken from \mathcal{L} for substituting the unreliable $Q(u_k[i])$ of the k-th data stream; 3) by combining 1) and 2) as the previous decisions, the tentative decisions of the following streams $\hat{b}_{k+1}[i], \ldots, \hat{b}_K[i]$ are subsequently obtained by the adaptive detector. Let us define the vector with the candidate constellation point as

$$\check{\mathbf{s}}_{k,m}[i] = \left[\hat{s}_1[i], \dots, \hat{s}_{k-1}[i], c_m\right]^T,$$
 (18)

$$= \left[\hat{\boldsymbol{s}}_{k-1}^{T}[i], c_{m}\right]^{T}.$$
(19)

Therefore, (5) turns out to be

$$\bar{\boldsymbol{r}}_{k+1,m}[i] = \left[\boldsymbol{r}^{T}[i], \check{\boldsymbol{s}}_{k,m}^{T}[i]\right]^{T}, k = 1, \dots, K.$$
(20)

The tentative decision of the (k + 1) stream becomes

$$\hat{b}_{k+1}[i] = \mathbf{Q} \Big\{ \tilde{\boldsymbol{\omega}}_{k+1}^{H}[i] \bar{\boldsymbol{r}}_{k+1,m}[i] \Big\}.$$
(21)

The CC algorithm selects the best constellation point among M candidates according to the maximum likelihood (ML) rule as

$$m_{\text{opt}} = \arg\min_{1 \le m \le M} \left\| \boldsymbol{r}[i] - \hat{\boldsymbol{H}} \boldsymbol{b}_k^m[i] \right\|^2.$$
(22)

Then c_{opt} replaces the unreliable decision $u_k[i]$. The same receive filter $\omega_k[i]$ is used to process all the candidates, which allows the proposed algorithm to have the simplicity of the adaptive DF detector. Here we employ an RLS algorithm to estimate the channel [8].

3.2. Computational Complexity

Let us define the parameter $K = N_R$, and M as the number of candidates. The numbers of complex multiplications, corresponding to the V-BLAST and the DF-RLS, are $2K^3 + K^2 + K$ and $\frac{28}{3}K^2 - \frac{4}{3}$. respectively. As for the proposed scheme, in the worst case², it requires $M(5/2K^2 - 3/2K)$ multiplications on top of the DF algorithm. The additional complexity is obtained by:

- If u_1 is unreliable, we replace $Q(u_1)$ with c_m , the multiplication repeats M times for the different c_m . The number of the complex multiplication is $M \times \sum_{k=1}^{K-1} k$.
- If u_2 is unreliable, as previously, the number of complex multiplications is $1 + M \times \sum_{k=1}^{K-2} k$.
- If u_3 is unreliable, the number of complex multiplications is $2 + M \times \sum_{k=1}^{K-3} k$.
- By summing across K users we have: $\sum_{k=1}^{K} (k-1) + M \sum_{k=1}^{K-k} k.$

The overall additional complexity can be obtained by summing the above figures with the complexity required by the ML selection rule and the reliability checking algorithm. Moreover, the probability of unreliable estimates decreases as the number of users increases³, which leads to the processing of 6.1%, 4.65%, 3.59% on average over the users of the estimated symbol for K = 2, 4, 8 users, respectively. The numerical results suggest that extra computations can be further reduced in larger systems where both N_R and K are larger.

3.3. Multiple-Branch Processing

In this subsection, the proposed detector is applied with several parallel branches that are equipped with different NCO patterns. Let us define $\hat{s}'[i] \triangleq T_l \hat{s}[i] = [\hat{s}_{1,l}[i], \hat{s}_{2,l}[i], \dots, \hat{s}_{K,l}]^T$, a permutation of the detected symbol set $\hat{s}[i]$, ordered by the transformation matrix $T_l, l = 1, \dots, L$, where each row and each column of T_l contain only one '1'. We also define $u_{k,l}[i]$ as the output of the k-th concatenated filter for the l-th branch which exploits the permutation matrix T_l . The detected symbols can be obtained in the original order by using $\hat{s}_l[i] = T_l^T \hat{s}'_l[i]$. The optimal ordering scheme conducts an exhaustive search of L = K!. Sub-optimal schemes have been proposed in [10] to design the codebook with a reduced L.

4. ITERATIVE DETECTION AND DECODING

In the following, a soft-output detector is described to improve the performance of the proposed detector in the concatenation with a convolutional code. Let $b_{k,j}$ be the *j*-th bit of the constellation symbol and $(j = 1, 2, ..., \log_2 C)$. We denote $L[b_{k,j}]$ as the log-likelihood ratio (LLR) value for the coded bits $b_{k,j}$. The *extrinsic* information is obtained by the detector as [12]

$$L[b_{k,j}^{(e1)}] = \ln \frac{\sum_{\boldsymbol{s} \in \mathcal{A}_{k,j}^{1} \cap \mathcal{B}} \mathsf{P}(\boldsymbol{r}|\boldsymbol{s}) \exp\left(f(\boldsymbol{s})\right)}{\sum_{\boldsymbol{s} \in \mathcal{A}_{k,j}^{0} \cap \mathcal{B}} \mathsf{P}(\boldsymbol{r}|\boldsymbol{s}) \exp\left(f(\boldsymbol{s})\right)}.$$
 (23)

and $\mathcal{A}_{k,j}^{1}$ is the set of all symbol vectors that consist of bits satisfying $b_{k,j} = 1$, $\mathcal{A}_{k,j}^{0}$ is similarly defined but satisfying $b_{k,j} = 0$. Similar to list-SD [12], a list of vectors can be found by deploying the proposed detector, the ML vector can be found as a tentative decision. By appropriately selecting the tentative decisions, the AMUDFCC detector performance can approach the optimal MLD performance. Let \mathcal{B} denote the set of tentative decisions obtained from

$$\mathcal{B} = \mathbf{B}_1 \cup \mathbf{B}_2 \cup \dots, \cup \mathbf{B}_k \cup \dots, \cup \mathbf{B}_K,$$
(24)

If L > 1, MB is used and we have

$$\mathcal{B} = \mathcal{B}_1 \cup \mathcal{B}_2 \cup, \dots, \cup \mathcal{B}_l \cup, \dots, \cup \mathcal{B}_L.$$
(25)

When the intersection set is empty, i.e. $\mathcal{A}_{k,j}^1 \cap \mathcal{B} = \emptyset$ or $\mathcal{A}_{k,j}^0 \cap \mathcal{B} = \emptyset$ the LLR for that specific bit can be filled with an arbitrary number with a large magnitude. The probability density can be obtained by $P(\boldsymbol{r}|\boldsymbol{s}) \propto \exp\left(-\frac{1}{\sigma_v^2}\|\boldsymbol{r} - \boldsymbol{H}\boldsymbol{s}\|^2\right)$, where $f(\boldsymbol{s}) = \frac{1}{2}(2\boldsymbol{b}_{[k,j]}^T - 1)\boldsymbol{L}[b_{k,j}^{(p1)}]$, where $b_{[k,j]}$ is the vector of all bits without the *j*-th bit from the *k*-th symbol, and similarly for the L-vector.

5. SIMULATION RESULTS

In this section, simulations are presented to demonstrate the system performance of the proposed AMUDFCC detection algorithm. We consider time-varying fading channels and QPSK modulation. The transmitted vectors s[i] are grouped into frames of 500 symbol vectors where the first 10 symbol vectors are training data and the column-norm based ordering described in Section 2 is employed.

 $^{^{2}}$ We have the worst case and the best case which means all K decisions are considered unreliable and all decisions are reliable, respectively.

³This is due to the increased overall detection diversity.



Fig. 3: Performance with $E_b/N_0 = 13$ dB, AMUDFCC with $d_{th} = 0.5$ and LS channel estimation. (a) AMUDFCC has a superior performance to the conventional DF scheme and is not far from the MLD performance obtained with the SD. (b) The AMUDFCC has a similar cost to the conventional DF.

In Fig.3(a), it is shown the BER performance against the number of users assuming $N_R = KN_T$ for a block fading channel. The BER performances of all schemes improve while the number of receive antenna N_R grows with the number of users K. More importantly, the proposed detector offers a significant performance gain over the DF-RLS detector at a small extra computational cost as shown in Fig.3(b). By adding more complexity, the performance can be further improved by introducing L parallel branches. The computational complexity is shown in terms of floating-point operations (FLOPS) per symbol detection.⁴



Fig. 4: MSE of the estimated symbols in terms of RLS iterations, with 4 users. After 10 training vectors, the decision-directed mode is switched on.

Fig. 4 illustrates the MSE for the symbol estimation across all 4 users in terms of RLS iterations. The channel between a transmit and receive antenna pair follows Jakes' model [13]. Here, we have $E_b/N_0 = 14$ dB and the normalized Doppler frequency shift equals $10^{-2.5}$, $10^{-2.75}$ and 10^{-3} , respectively. It is clear that the AMUDFCC-RLS considerably reduces the MSE level when compared to DF-RLS. For a coded system with RLS channel estimation, the BER performance against the average SNR across all users is shown in Fig.5. The curves show that the proposed AMUDFCC detector has a substantial performance gain as compared to the conventional DF scheme. By increasing the number of branches with different NCO, the SD performance can be approached.

⁴The FLOPS were counted by the Lightspeed toolbox [13]. The FLOPS count as 2 for a complex addition and as 6 for a complex multiplication.



Fig. 5: K = 6 users are separately coded by the $g = (7, 5)_o$, rate R = 1/2, memory 2 convolutional code and we use the block size equals 500 vectors, M = 4 candidates and $d_{\text{th}} = 0.5$. The number of turbo iterations between the detector and the decoder is 3.

6. CONCLUSIONS

In this paper, we have developed an adaptive iterative decision feedback based detector for MU-MIMO systems in time-varying channel. The proposed scheme is able to approach the optimal MLD performance while requiring a significantly lower computational cost.

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