Performance Evaluation of Loose Beamforming Using Direct-Binary Search in Massive MIMO Systems

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***Abstract*—When considering beamforming in massive MIMO systems, the large number of antennas increases the amount of calculation at a base station. There is also a concern about the complexity of antenna circuits. Therefore, we have proposed loose beamforming in which the beam is formed by deciding whether or not to use the antenna for each user. However, an appropriate antenna selection method for the loose beamforming has not been established yet. In this study, we introduce a direct-binary search into the generation of the loose beamforming weights and evaluate the performance. Although the throughput is lower than one of other optimization methods such as a genetic algorithm, it can significantly reduce the computation time and can generate appropriate weights for a short time, thereby confirming the effectiveness of the proposed method.**

***Index Terms*—Loose beamforming, Massive MIMO, Antenna selection, Direct-binary search, Local optimal solutions**

I. Introduction

The commercialization of the 5th generation mobile communication (5G) system has begun, and research on next generation communication systems such as Beyond 5G and 6th generation mobile communication (6G) is underway. In 5G and 6G, Massive MIMO systems [1] that deploy hundreds of transmitting antenna elements at a base station (BS) are being considered in order to increase channel capacity and data transmission speed in the high frequency band. This system has attracted attention as an important technology in the realization of 6G.

Conventionally, in MIMO systems, a precoding method that uses all antenna elements to generate transmit weights, such as the Minimum Mean Square Error (MMSE), has been used for beamforming. However, Massive MIMO system has a large number of transmit antenna elements, which increases the amount of computation. In addition, since all antenna elements are used in conventional methods, phase shifters and amplifiers are required according to the number of elements. This makes high frequency circuits more complex.

To solve these problems, antenna selection in RF circuit reduction has being researched [2]-[4]. Many studies using antenna selection insist the technique can improve system complexity and hardware cost. However, as previously stated, this technique requires circuits to control phase and amplitude for beamforming. Therefore, we have proposed loose beamforming [5]-[9]. In the loose beamforming, the antenna elements are selected in order to form a quasi-optimal beam for each user. It is one of the beamforming methods that uses the channel response as it is. This method may greatly reduce the amount of calculations for precoding because the loose beamforming can be done only by turning the antennas on and off. In addition, since a switch is placed at each antenna instead of a circuit that controls complex amplitudes, it is expected to simplify the high-frequency circuitry and reduce costs. This means that if this method is established, low-computation and low-cost beamforming will be possible.

However, the optimal weight generation method for loose beamforming has not been currently established. In other words, the appropriate antenna selection method is not known. The problem of finding loose beamforming weights is a combinatorial optimization problem. In Massive MIMO systems with hundreds of antenna elements, the number of combinations is enormous. Therefore, mathematical optimization methods such as a genetic algorithm (GA) have been used to generate quasi-optimal weights. The loose beamforming weights generated by the mathematical optimization method gives good performance, but a lot of calculation time is required. Considering practicality, this method is not suitable for beamforming that requires real-time processing.

In this study, we are adapting direct-binary search (DBS) [8]-[10] to generate loose beamforming weights. DBS is expected to reduce computation time because of its simpler processing. The literature [8], [9] are the first papers applying DBS to loose beamforming. This paper summarizes the concept of them. Also, [10] proposed utilizing the DBS as 01 optimization for optical devices. This paper shows the performance of the loose beamforming using DBS and evaluates.

II. Loose beamforming using DBS

A. Loose beamforming

In this paper, we consider beamforming on the downlink in a Massive MIMO system with N transmit antenna elements in BS and K receiving users. We define $\boldsymbol{H}$ as a $K \times N$ channel matrix between the BS and K users, $\boldsymbol{s}$ as the K dimensional transmission signal vector, and $\boldsymbol{n}$ as the K dimensional noise

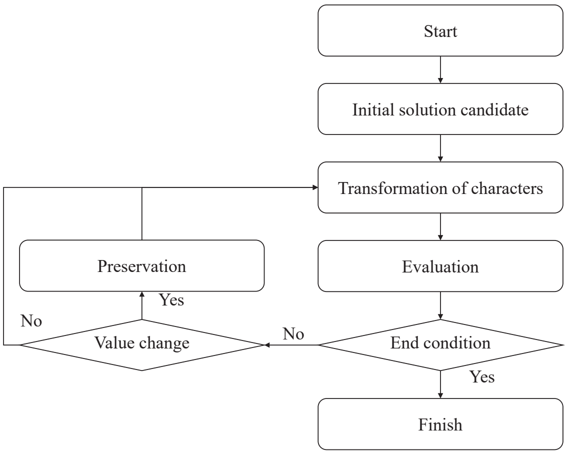

Fig. 1: Flowchart of DBS

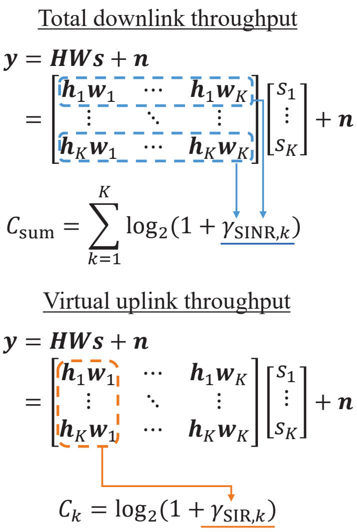

Fig. 2: Difference in evaluation function

vector for each UE. Then, the K dimensional received signal vector $\boldsymbol{y}$ is given by

$$\boldsymbol{y} = \boldsymbol{HWs} + \boldsymbol{n}. \tag{1}$$

Loose beamforming is a concept of selecting some useful antenna elements instead of weight calculation of all the elements. The weight matrix $\boldsymbol{W}$ produced by loose beamforming are defined by

$$\boldsymbol{W} = \begin{pmatrix} w_{11} & \cdots & w_{1K} \\ \vdots & \ddots & \vdots \\ w_{1N} & \cdots & w_{NK} \end{pmatrix}. \tag{2}$$

For each element of loose beamforming weight matrix, w_{nk} = 1 and 0 denote that antenna is used and not used, respectively. In this paper, we apply DBS for searching a quasi-optimal solution of (2).

B. DBS

The elements of the weight matrix $w_{n,k}$ are determined so that the evaluation functions (3) and / or (4) are maximized. The optimal weight can be determined by trying all possible combinations of 0s and 1s. However, as the number of BS transmitting antenna elements and the number of users increase, the number of combinations increases dramatically, and the solution cannot be obtained in a realistic amount of time. This is a so-called combinatorial explosion. Therefore, DBS determines the 0s and 1s of the elements of the weight matrix by a method described below, and searches for a combination that approaches the maximum value of the evaluation function as much as possible.

A flowchart of DBS is shown in Fig. 1. First, initial solution candidates are generated. In this paper, its elements are chosen randomly to be 0 or 1. Next, one element of the candidates is randomly selected and a state change is applied to that element. Then, evaluation is performed according to the evaluation function. If that change in state improves the evaluation value, hold that state. Conversely, when the evaluation value is worse, the state change is discarded. By repeating this process, optimization can proceed while keeping the best. In this paper, testing all the elements once is defined as one iteration.

To evaluate loose beamforming weights, the following evaluation functions

$$C_{\text{sum}} = \sum_{k=1}^{K} \log_2(1 + \gamma_{\text{SINR},k}) \tag{3}$$

$$C_k = \log_2(1 + \gamma_{\text{SIR},k}). \tag{4}$$

where $\gamma_{\text{SINR},k}$ and $\gamma_{\text{SIR},k}$ are the signal-to-interference-plus-noise ratio (SINR) and signal-to-interference ratio (SIR) for the kth user, respectively. The differences in evaluation functions are shown in Fig. 2. In the figure, $\boldsymbol{h}_k$ is kth row vector of $\boldsymbol{H}$, and $\boldsymbol{w}_k$ is kth column vector of $\boldsymbol{W}$. Equation (3) uses the row elements of the execution channel matrix to compute the SINR, on the other hand, (4) uses the column elements of the execution channel matrix to compute the SIR. $\gamma_{\text{SINR},k}$ is calculated by (5) and $\gamma_{\text{SIR},k}$by (6)

$$\gamma_{\text{SINR},k} = \frac{|\boldsymbol{h}_k \boldsymbol{w}_k|^2}{\sum_{i=1,i\neq k}^{K} |\boldsymbol{h}_i \boldsymbol{w}_k|^2 + \sigma^2} \tag{5}$$

$$\gamma_{\text{SIR},k} = \frac{|\boldsymbol{h}_k \boldsymbol{w}_k|^2}{\sum_{i=1,i\neq k}^{K} |\boldsymbol{h}_i \boldsymbol{w}_k|^2}, \tag{6}$$

where σ^2 is the noise power of the user terminal.

Equation (3) is the total downlink throughput. Maximizing this equation is equivalent to minimizing interference at the receiver. Equation (4) calculates the virtual uplink throughput for the kth user [11]. Maximizing this equation corresponds to minimizing interference to other users on the transmit side. Equation (3) requires that a weight must be fully generated to calculate throughput. The number of elements is $N \times K$, and we need to deal with such a large number. On the other hand, (4) does not require full weights to calculate throughput, because the throughput can be calculated using only the desired signal of the kth user and the interfering signal to other users. The number of elements is N, which greatly reduces the number of elements compared to (3). The

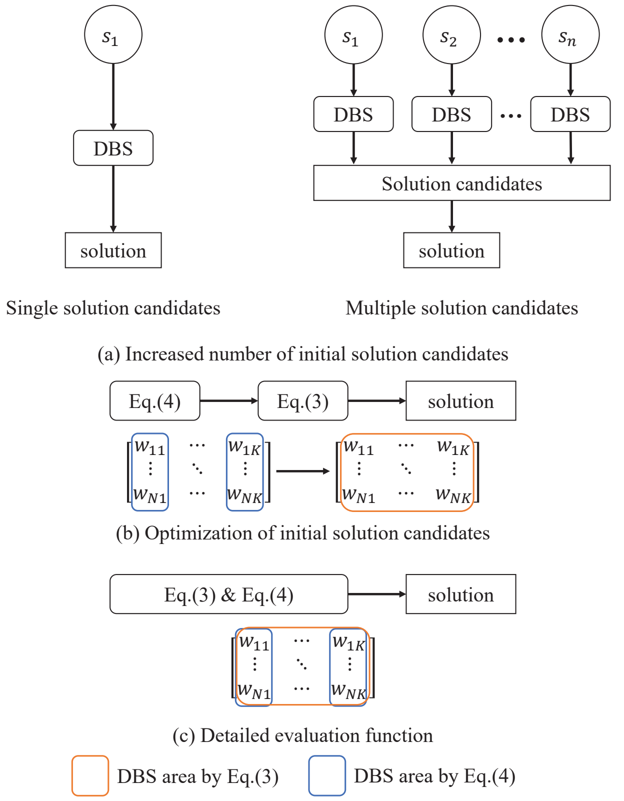

Fig. 3: Proposed countermeasure

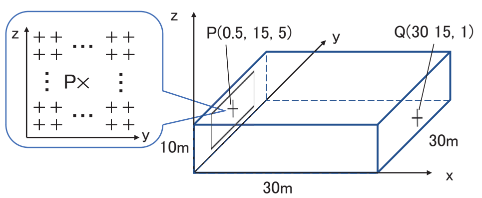

Fig. 4: Simulation environments

reduction in the number of elements narrows the solution search space. It is expected that this will make it easier to find the optimal solution.

In this paper, we use DBS to generate loose beamforming weights defined (2). For example, if the element w_{nk}element is 0, it is changed to 1. Then, we evaluate the throughput using (3) or (4). If the evaluation value has improved, retain the state change. If it has worsened, discard it. The same process is performed also for the case where the w_{nk} element is 1.

C. DBS Issues and Measures

Since DBS is a simple algorithm, it is expected to reduce computation time. On the other hand, it has no method of escaping from local optimal solutions such as mutation of GA. Therefore, there is a problem of solution depending on the initial solution candidates and the order of reversal. Especially in loose beamforming in Massive MIMO systems, it is necessary to consider measures to prevent this problem, because the large solution space makes it easy to fall into local optimal solutions.

In this paper, we propose three countermeasures taking account of the increase in the amount of computation. Each of the proposed measures is called method (a), (b), or (c), and a schematic diagram is shown in Fig. 3. The first is to increase the number of initial solution candidates as shown in Fig. 3 (a) (Multiple solution candidates). This achieves apparent multi-directional optimization. By increasing them, the diversity of solutions can be multiplied, thus improving the expected performance. The second proposal uses pre-optimized weights as initial solution candidates as shown in Fig. 3 (b). Each column of weights is optimized using (4) to reduce interference to each user. Then (3) optimizes the entire matrix to suppress the interference. It should be noted that this approach uses two DBS with different evaluation functions. The third is to give DBS two evaluation functions as shown in Fig. 3 (c). We use (3) and (4) at the same time to hold the inverted state when both downlink and uplink throughput are improved. It should be noted that the difference between method (b) and method (c) is whether the evaluation functions (3) and (4) are used separately or simultaneously.

III. Simulations and Results

A. Simulation Environments

In this study, an indoor environment of 30 m length, 30 m width, and 10 m height is assumed, as shown in Fig. 4. The building materials are concrete and there are neither fixtures nor windows, for simplicity. It is within line of sight from the BS to all users. The detailed material properties are as follows : relative permittivity ϵ_r=6.76, electrical conductivity σ=0.0023 S/m, and permeability μ_r=1. The BS is an array of 10 $\times$ 10 antenna elements, whose radiation pattern is similar to that of dipole. It is placed on the wall as shown in Fig. 4. The antenna spacing is half-wavelength and the carrier frequency is 5 GHz. Ten receiving users are randomly located, and each user has one antenna. For simplicity, the effects of coupling between antenna elements and human blockages during signal transmission are assumed to be absent. The noise power of each receiving device is assumed to be the same for all users, and the SNR due to only the direct wave is assumed to be 20 dB when a signal is transmitted from the point P at the center of the BS array to the point Q on the opposite wall surface in Fig. 4.

In the above environment, we obtain channel matrices between the BS and UE by using Raplab [12], which is software for radio propagation analysis using a ray-tracing technique. Furthermore, the number of trials is set to 100.

B. Simulation results

Fig. 5 shows the total downlink throughput performance of loose beamforming with DBS. As a comparison, the performance of MMSE for normal beamforming and loose beamforming using GA [5], quantum annealing [6] and simulated annealing [7] are shown. It is noted that the MMSE performance is the best because it optimally controls the

TABLE I: Weight generation time

Evaluation functions	Generation time[s]
MMSE	1.4×10^{-3}
DBS(Eq.(4))	97×10^{-3}
DBS(Eq.(3))	213×10^{-3}
SA	11
QA	30
GA	396

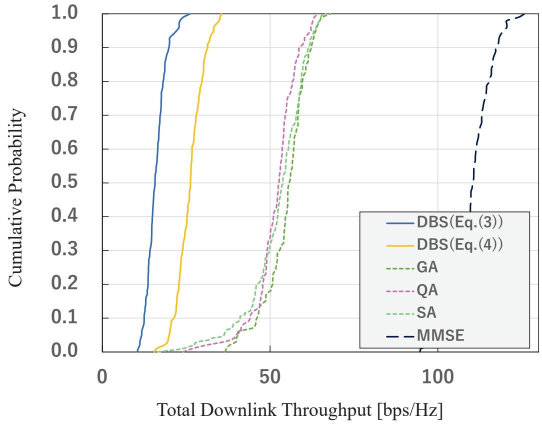

Fig. 5: Total downlink thoughput

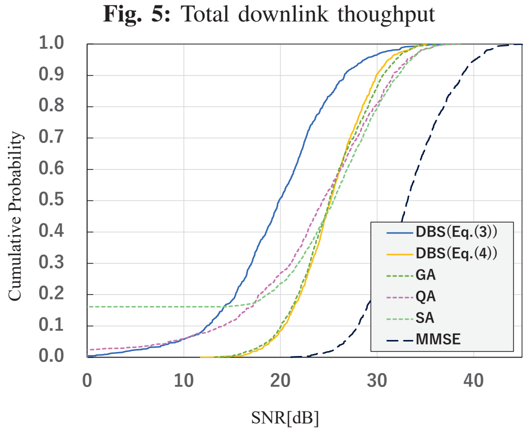

Fig. 6: SNR performance

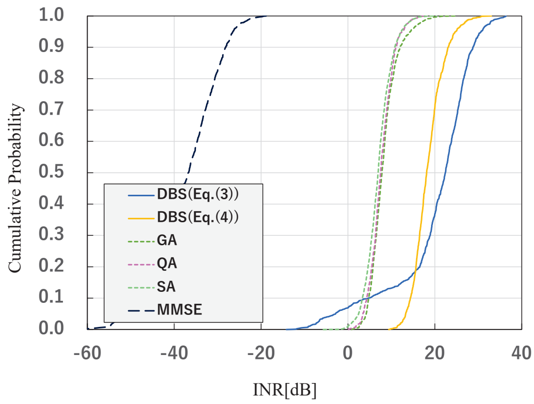

Fig. 7: INR performance

amplitude and phase of all the antenna elements. As for the two evaluation functions considered in this study, loose beamforming using (4) showed higher throughput. We think the reason for this result is the different size of the solution space. As mentioned earlier, the number of elements is $N \times K$ when (3) is used, and N elements when (4) is used. We consider that the above result has been obtained because using (4) narrows the solution space and makes it easier to find the optimal solution. Figs. 6 and 7 show the SNR and INR performance, respectively. The throughput improvement is due to suppression interference. Fig. 6 shows that using (4) improves SNR over (3). The reason for this result is that the desired signal can be strengthened for the users by using (4). In Fig. 7, there is a range where interference is better suppressed using (3). The reason is that in DBS using (3), the desired signal is strengthened or interference is suppressed in order to improve the total throughput. Therefore, good interference suppression is achieved with a certain probability. However, compared with (4), it cannot be optimized for each user and may not take account of some user's desired signal or interfering signal. Therefore, the performance are generally degraded when using (3).

Moreover, Fig. 8 shows the results when the number of iterations is increased. The "ite" in the figure represents the number of iterations. The total downlink throughput performance improves as the number of iterations increases, but the change becomes smaller after a certain number of iterations. This is due to the DBS algorithm. As mentioned in II.C, DBS is prone to converge to local optimal solutions because of its simplicity. As the number of iterations increases, the weights become more optimized, but the possibility of falling into a local solution increases. This is shown in Fig. 8, where the change in performance becomes small after a certain number of iterations. This suggests that a local solution has been achieved, and an increase in the number of iterations alone is not expected to improve the performance.

Therefore, the performance of the three methods in II.C proposed to improve the search capability of DBS is shown in Fig. 9. In method (a), the number of initial solution candidates is set to 10 and the evaluation function used is (4). The number of iterations for all methods is 1. All of the methods designed to solve the DBS issues produce better results than the normal DBS. Increasing solution diversity, adjusting initial solution candidates and giving detailed evaluation functions are found to improve DBS's ability to search for solutions. In particular, the method (c) gives the best results, and we can say that the choice of the evaluation function for DBS is an important factor.

The performance is worse than the other optimization methods such as GA, but DBS has an advantage in computation time, which can be reduced by a factor of about 1/100 to 1/1000. We think this factor depends on the number of times needed for throughput calculations. In GA, the number of throughput calculations is approximately the number of generations multiplied by the number of individuals. In the simulation, the number of generations was 10000 and the number of individuals was 200. Thus, GA calculated the throughput 2000000 times. On the other hand, the number of DBS throughput calculations is the number of elements.

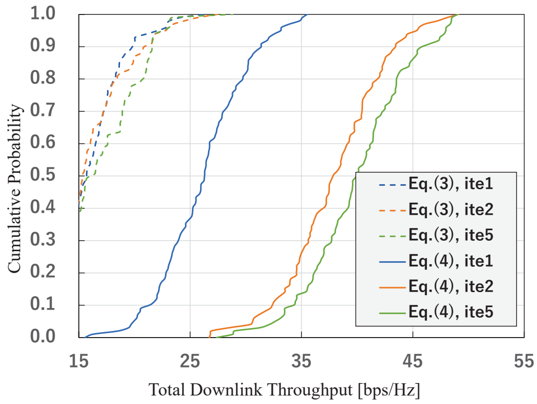

Fig. 8: Difference of iterations

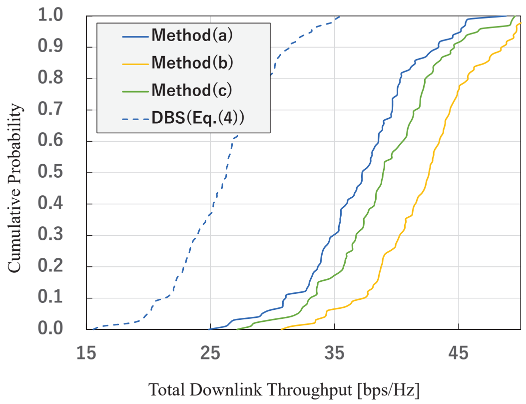

Fig. 9: Performance comparison between countermeasures

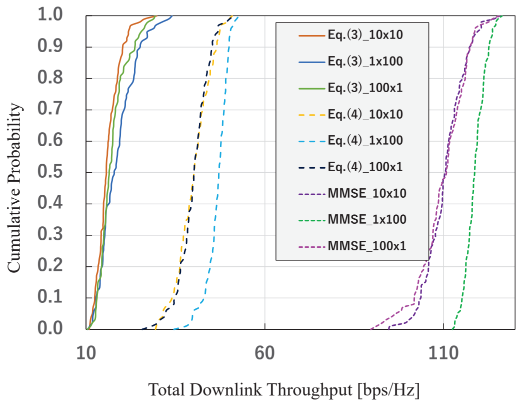

Fig. 10: Effect of array shape variation

According to this simulation, the number of times was 1000. The number of calculations is reduced by 1/2000. Although there is an error due to coding, the amount of calculation is reduced. In addition, the performance of DBS is degraded when compared to the performance of annealing. Quantum annealing requires a quantum computer to conduct the calculation. This is the cost of setting up the antenna, and loses the advantage of loose beamforming. It is possible to entrust the process to a quantum computer in the cloud, but it would take time to do processing other than generating weights. In fact, the quantum annealing result shown here was obtained using D-Wave's quantum computer [13]. The computer gets the results by exchanging files in the cloud, but this takes time. Simulated annealing can be computed on a classical computer, but the difference in computation time is higher than that of DBS. In beamforming, weights must be generated in a short time in practical applications. From the above, DBS is an effective method that satisfies the advantages of loose beamforming. Table I shows the time to generate weights. Using (4) takes less time than (3) because the former requires fewer matrix calculations for obtaining throughput. Equation (4) can be computed for each user, so parallel processing is also possible. Therefore, we believe that its application to multi user MIMO is also effective.

C. Effect of array shape variation

Once a method of antenna selection for loose beamforming is established, low-computation and low-cost beamforming can be realized, but there are still many uncertainties. In order to clarify the method, it is necessary to evaluate the performance under a variety of conditions and environments. Here, we consider effect of array shape variation. We change the array shape and see if we have changes in the performance. In this simulation, three types of array shapes are compared: 10×10, 1×100, and 100×1. The 1×100 array has elements placed horizontally and the 100×1 array has elements set vertically. Fig. 10 shows the total downlink throughput performance for the different array shapes. In this simulation, (3) and (4) are used for the DBS's evaluation function. The performance of MMSE is also shown for comparison. Overall, changing the array shape does not show large effect on the performance. However, for the array with 100 elements in the horizontal direction, (4) and MMSE improve the performance. The results show that loose beamforming exhibits similar change of performance to normal beamforming.

IV. Conclusions

In this paper, we have proposed and a loose beamforming using DBS in a Massive MIMO system and evaluated the performance. The performance is highly variable depending on the evaluation function used. In particular, the solution search capability can be improved by providing detailed evaluation functions. Compare to other optimization methods such as GA, we confirm that although the performance is not as good as that of GA, the computation time can be greatly reduced and appropriate weights can be generated for a shorter time. From the above, we state that DBS is an effective method for loose beamforming. In addition, simulations are performed with varying the array shape to examine the detailed performance of the loose beamforming. In the environment stated here, the change in performance is similar to MMSE. However, to establish loose beamforming, it is necessary to analyze simulations in other environments as well. For example, environments with a channel estimation errors should be examined. It also needs to be tested in an environment with obstacles. Fewer paths may reduce the number of cases in antenna selection, and then the number of 01 combinations.

As a result, we expect to find better solutions even with simple optimization methods such as DBS. Future prospects is to find the optimal antenna selection method.

Acknowledgment

This work has been supported by JSPS KAKENHI Grant Number JP23H00474.

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