OA-Loc: Supporting Virtual Users in Outdoor Assisted Indoor Localization

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***Abstract*—The rapid development of mobile devices and mobile Internet increases demands for location-based services. In outdoor environments, the mobile devices can obtain precise positioning through GPS localization. While in indoor environments, it is difficult to receive GPS signal. Researchers have proposed many methods to produce relative position rather than physical position. In this paper, we propose a new localization approach called OA-Loc which utilizes outdoor mobile devices' GPS information for precise reference points. And with the RSSI between outdoor and indoor devices it could help the latter to obtain physical position. We analyze in detail the working principle of the approach, and provide a detailed design. We also implement our technique on mobile devices and evaluate it in real-world scenarios. The results show that our approach has high feasibility and decent accuracy.**

***Index Terms*—indoor localization, mobile devices, outdoor assisted**

I. INTRODUCTION

With the popularization of smart mobile devices and development of mobile Internet, the demands for positioning and navigation grow very quickly. Especially in some environments, such as large shopping malls, with indoor navigation, one can quickly find the exit or elevator and parents can also track the position of their children to avoid them wandering off. For Smart Home applications, merchants bring more introductions about the LBS-enabled products which provide users with services based on their specific locations. In outdoor environments, mobile devices can obtain precise positioning by means of GPS locating. However, line of sight (LOS) is required for the functioning of the GPS devices. This leads to inability to use GPS for an indoor environment where the LOS is blocked by walls and roofs. Although base station based locating can be utilized but its accuracy is too low to meet the requirements, and indoor environment is complex and volatile. These have motivated a large body of research on indoor localization. For example, there has been a focus on leveraging existing infrastructure (e.g., Wi-Fi access points) to enable indoor localization. The advantage of these approaches is the cost of deploying a specialized infrastructure for localization is avoided. However, some of them generally require extensive pre-deployment efforts such as to build detailed RF map or RF propagation models based on the surveys of site [1]. Site survey is time-consuming, labor-intensive, and easily affected by environment dynamics [2]. There are also some approaches need to deploy specialized infrastructure [3] to achieve positioning. Although it is possible to obtain a high positioning accuracy, the cost of the system will be very high. In addition, there have methods combining GPS technique and base station locating for localization [4]. These approaches can reduce the search time of the GPS, but in case of none-base station environments they may not be able to work.

To avoid disadvantage of these localization approaches, we propose an indoor localization method with outdoor assistance called OA-Loc which takes advantages of outdoor GPS-enabled mobile devices. Nowadays, the widespread use of high-precision GPS enables mobile devices as reference points with latitude and longitude coordination. The indoor mobile devices waiting for localization keep broadcasting requirements through Wi-Fi interface. Once an outdoor mobile device accepts the requirement they will communicate with each other for the data of coordinates and RSSI values through wireless communication means. Finally, the combination of localization algorithms can get the coordinates of the indoor mobile devices. The OA-Loc requires no pre-deployed infrastructures but only uses mobile devices and existing mature technologies as GPS and Wi-Fi communication can be easily found on nowadays mobile devices. And another key advantage is its cost is low, because almost every person carries one or more mobile devices, such as smartphones and pads. The OA-Loc relies on four basic assumptions: (1) users carry mobile devices, equipped with a wireless communication function, such as Wi-Fi, (2) outdoor mobile devices shall be equipped with a GPS module, (3) indoor devices must receive three or more relevant data which provided by outdoor devices within a certain time interval, (4) the technical specifications of the wireless communication means between indoor and outdoor devices determines the accuracy and pointing area.

II. RELATED WORKS

Indoor localization has been an active area of research in recent years. Many researchers have conducted a lot of research contributions to this area, and proposed some representative research results. In this section, we provide a brief overview of representative work in this area.

Localization using GPS: The Global Positioning

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System (GPS) is a satellite-based navigation system. The GPS system consists of three parts: the space part, the control panel and the users (receivers) [5]. The space part consists of 24 satellites. GPS satellites send navigation messages continuously at a rate of 20 bits per second. The users utilize these messages for localization. The control panel is composed of a number of tracking stations, they are used to track, maintain and monitor space satellites, and maintain orbit of the satellite. The user part consists of GPS receivers, data processing software and the corresponding user devices such as smart phones. They are used to receive messages from GPS satellites, and calculate the users' location. The basic principle of GPS is to calculate the transfer time of each message and multiply by the speed of light to compute the distance to the satellite. With three or more satellites, we can obtain a set of positioning equations. After calculation we can obtain the user's location. The advantage of GPS is that receivers can determine latitude, longitude, and altitude to a high degree of accuracy. However, line of sight (LOS) is required for the functioning of GPS. This leads to inability to use GPS for an indoor environment where the LOS is blocked by walls and roofs. After adding some special hardware devices, GPS can be used in indoor environment [6], but the cost of system becomes high.

RSSI-based localization: these approaches leverage existing infrastructure such as Wi-Fi access points, base station, and so on. There are many kinds of Wi-Fi signal based indoor localization approaches. A majority of them employ Received Signal Strength Indicator (RSSI) of access point as a metric for location determination. RSSI fingerprinting based localization [7], model-based localization [8] and probability distribution localization [9] are commonly used WiFi-based indoor localization. The company of Qubulus has developed an engine for indoor localization by building a RSSI fingerprint database. The locating process of these approaches is usually divided into two phases: the offline phase and online phase. In the first phase, through an environment survey process, the system builds a fingerprint database. In the online phase, the users can send a query with their current RSSI fingerprint. If there has the matched fingerprints in fingerprint database, the users can get their corresponding locations. The RADAR system [1] developed by Microsoft, also makes use of Wi-Fi. The system builds a signal propagation model from the mobile device to the access point. Because of indoor reflection and multipath effects, model-based localization approaches often have low performance [10]. While RSSI fingerprinting based localization approaches can achieve good performance [1], but they require extensive pre-deployment efforts. In other words, we should collect adequate data in offline phase. So many researchers set out to solve how to ensure reliability of fingerprint database without increasing workload in offline phase. However, these methods cannot avoid effects from surroundings.

INS-based localization: INS (Inertial Navigation System) is a self-contained navigation system. It does not rely on external information, and do not radiate energy. The measurements provided by accelerometers, gyroscopes and compass are used to track the position and orientation of an object relative to a known starting point, orientation and velocity [5]. If the initial position is not known, only the relative position to the origin can be determined. With the continuous development of hardware technology, these sensors have been widely used in the terminal devices. The features of INS are to take full advantage of the hardware which are in the terminal devices, and does not need an external source of information. However, the error will increase over time, while the accuracy will decrease. Therefore, the INS can track the device movement over time, but needs calibration provided by another system.

Other methods that require special infrastructure: there are many other methods rely on deploying specialized infrastructure to enable indoor localization. For instance, Nokia proposed a location technique called High Accuracy Indoor Positioning (HAIP) which uses directional positioning beacons and receivers to perform localization. The HAIP is based on Bluetooth Low Energy (BLE) technology. The Active Badge [11] developed by AT&T uses infrared beacons and receivers to achieve localization. In recent years, with the rapid development of RFID technology, there have been a lot of RFID-based indoor positioning systems, such as LandMark positioning system [12] which is one of the outstanding representatives. They use densely arranged reference nodes in RFID network to achieve positioning. These methods generally require extensive deployment of specialized infrastructure, resulting in the high cost of the system, and need lots of pre-deployment efforts.

As described above, we can obtain a high positioning accuracy in outdoor environment by GPS, but not in indoor environment. According to this characteristic, we propose indoor localization with outdoor assistance called OA-Loc. In other words, it uses location information of outdoor users to assist the user in indoor environment to achieve localization. The two sides can interact through wireless communication function, such as Wi-Fi, Bluetooth. Compared to prior work, OA-Loc takes full advantage of the widespread use of mobile devices, does not require additional infrastructure. OA-Loc does not need any pre-deployment effort and knowledge of the floor plan. And the localization is performed in terms of absolute coordinates: latitude and longitude.

III. Localization Using OA-Loc

A. *Workflow of OA-Loc*

OA-Loc is based on a peer-to-peer architecture and increase the participation of the users. Fig. 1 shows the applications scenario of OA-Loc. The user in green is an indoor user waiting for localization while there are two users in yellow and blue respectively outside. Outdoor users get their position through GPS satellites and communicate with the indoor user via Wi-Fi channel. By measuring the signal strength between indoor and outdoor users we can predict relative distance between them. By using centroid based algorithm we will finally get the

physical position of the indoor user. However, there might not be at least three users simultaneously to provide GPS information. To solve the problem, OA-Loc brings forward virtual users to support the algorithm. As shown in fig.1, by utilizing the movement of user A, it acts as two different users asynchronously. We regard the latter user A as a virtual user. By supporting virtual users, OA-Loc will introduce latency but in many cases it is acceptable. When processing RSSI based algorithm, OA-Loc consults other algorithms to reduce errors.

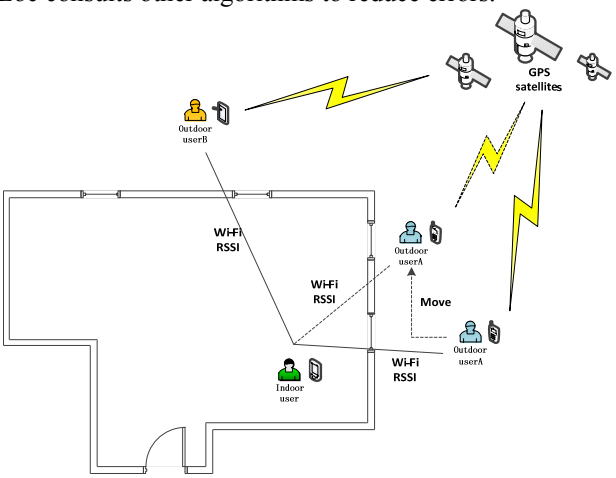

Figure1. The OA-Loc architecture.

Before describing the workflow of OA-Loc, we introduce the basic model of the OA-Loc. The model consists of outdoor users $User_{out} = \{U_1^o, U_2^o, ..., U_n^o\}$ and indoor users $User_{in} = \{U_1^i, U_2^i, ..., U_n^i\}$, where U_j^o is the jth outdoor user and U_j^i is the jth indoor user. $Position = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ stands for all position of the outdoor users, where (x_j, y_j) is the jth outdoor user's position. The outdoor users need a certain communication means to send the position information to the indoor user, such as Wi-Fi, Bluetooth, etc. In this paper, we use Wi-Fi to connect both users. Before positioning process starts, indoor users must turn on portable Wi-Fi hotspot functionality on mobile devices. When the hotspot is active, outdoor users' mobile devices can be directly connected to the hotspot without authentication. Through this link, they can interact with each other by Socket technique. In the communication, indoor devices act as a server and receive data. As a client, outdoor devices will forwardly send data. The following reasons describe why we use Wi-Fi rather than Bluetooth in this paper: (1) Wi-Fi is IP based, can interact with other IP-based devices naturally, (2) Wi-Fi has a greater range of services, (3) Wi-Fi has fine transfer rate. Due to the indoor devices acting as a hotspot, an outdoor device measure RSSI value from the hotspot. All measurements can be composed of a data set of RSSI: $RSSI = \{rssi_1, rssi_2, ..., rssi_n\}$, where $rssi_j$ is the RSSI value measures by the jth outdoor device. The common algorithm is described as in Algorithm 1. The indoor user receives several RSSI values from outdoor users and computes the physical location. Now, we will describe two different scenarios.

Algorithm 1 LocationOutDoorAssit (*x, y, R, N*)

```
X ←Φ, Y ←Φ, RSSI ←Φ, P ←Φ
while(TRUE)
X_i, Y_i, RSSI_i ← LocationReceive (X, Y, R)
if i equals to N
P ← LocationAlgorithm (X, Y, RSSI)
return P
end if
end while
end function
```

1) Real localization: In the first scenario, there are more than one user holding mobile devices in the outdoor environment. That is, the so-called real localization. The reference points come from different outdoor users. For outdoor users, they can get their accurate location by GPS devices. Then they try to connect to the hotspot set up by the indoor user and measure RSSI value. Finally, outdoor devices send the data of GPS and RSSI to the indoor device.

The indoor device acts as a server, waiting for the corresponding data from outdoor devices. When the indoor device has received at least three different samples from outdoor devices within a certain time interval, then combine with the specific positioning algorithm such as Trilateration Algorithm [13], Weighted Centroid Algorithm based on RSSI [14]. Hence, the indoor user position can be obtained.

2) Virtual localization: In most cases, there aren't always adequate users outside who can provide help. Sometimes, they hesitate to provide GPS data because they concern about privacy. In this paper, we bring forward virtual users strategy, namely, using one real user to simulate several virtual users. It is called virtual localization. In this scenario, the outdoor user should keep moving for assisting indoor user to achieve positioning. In this process of walking, outdoor device send data of GPS and RSSI to indoor device continuously. When indoor device has received more than three copies of different data, it combines them with the specific positioning algorithm. In this paper, we will use Weighted Centroid Algorithm based on RSSI for localization. It will be discussed in detail in the following section.

B. Weighted Centroid Algorithm Based on RSSI

Centroid Localization Algorithm in wireless sensor networks [15] is entirely dependent on the connectivity of network which works by calculating the geometric centroid of all the anchor nodes to estimate the unknown node position. In RSSI-Based Localization Algorithm, the signal strength of transmitting node is known. Then it calculates the propagation loss of the signal based on the received signal strength. Through theoretical and empirical model it converts propagation loss into distance. The Weighted Centroid Algorithm based on RSSI is combination of two previous methods. It works by calculating the geometric centroid of all the measuring points weighting each point's x and y coordinates by the signal strength measured. Obviously, the algorithm can be applied to the positioning method which proposed in

this paper. In this paper, outdoor devices are the anchor nodes and the indoor device is the unknown node.

In the following description, we call indoor device as the unknown node, outdoor devices as the known nodes. In $Position = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ The component of x represents the latitude coordinate and y represents the longitude coordinate. Two components divide the set of position into two sets. The set of x component: $X = \{x_1, x_2, ..., x_n\}$ and the set of y component: $Y = \{y_1, y_2, ..., y_n\}$. Each RSSI value in the measurement data set is processed as the following way:

$$rssip_j = \left(P_{ref} \times 10^{\frac{rssi_j}{20}} \right)^g \tag{1}$$

Where *rssip* means prioritized RSSI and P_{ref} is the reference power, the value of P_{ref} is 1mW. With this formula, the set of RSSI is converted to the set of RSSIP. In the formula where g is a constant that defines how big the weight difference between the highest and the lowest value should be. In other words, if the value of g is greater, the importance of a very small value of the RSSI is lower. Given a set of the known nodes with the data X, Y and RSSIP, the formula used for the calculation of the unknown node sounds as follows:

$$Pos = \left(\sum_{i=1}^{n} w_i x_i, \sum_{i=1}^{n} w_i y_i, \right) \tag{2}$$

Where w_i is the weight by which each RSSI is prioritized. The w_i is calculated as:

$$w_i = \frac{rssip_i}{\sum_{i=1}^{n} rssip_i} \tag{3}$$

There are two problems when it comes to using the algorithm described above in practice. The first problem is the ideal selection of the constant g. This constant relates to the specific environment, we will try to find the best value through specific experiments. The second problem is the distribution of the known nodes. We can get accurate results when the known nodes are more or less evenly distributed around the unknown node. This is because the geometric centroid of the known nodes only within the scope of them. For getting the more accurate results, we should solve these problems. The performance of this approach is evaluated in Section IV.

C. Selection of Reference Nodes

Reference nodes are fundamental parts of the centroid algorithm. They seriously affect the accuracy of locating. The idea circumstance is that reference nodes distribute evenly around the object node. We propose a method to optimize the selection of reference nodes as described below:

1) First, build the mapping between reference nodes and RSSI values and get two sets: set of RSSI values and set of nodes coordinates.
2) Second, use cluster algorithms to process these coordinates. The algorithm is shown as below.

Algorithm 2 SelectionNodes (*x, y*)

1: Choose two nodes in X coordinates with maximum difference
2: Set a threshold Δx based on that two nodes, divide reference nodes into two groups
3: Repeat same procedure to Y coordinates
4: Finally select m nodes in decreasing order of RSSI values from acquired four partitions

As seen in fig. 2, nodes selected using our algorithm will have better distribution around the target node. The algorithm also filters out many other nodes with low RSSI values. In general, higher RSSI value will introduce less error in locating. It can be seen in fig.2, the partition is obviously not based on geometry or number of nodes.

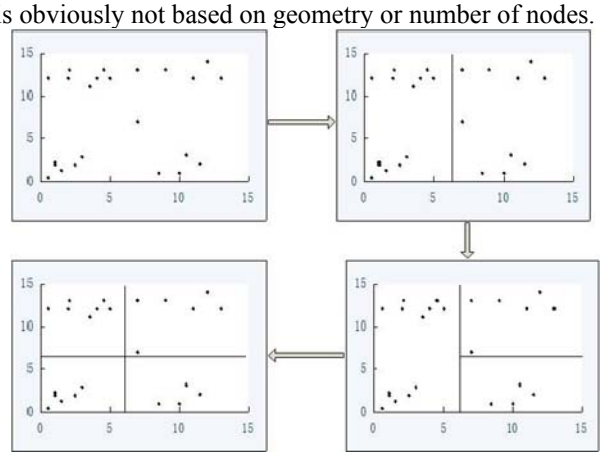

Figure2. Optimizing of selection of reference nodes.

We select m nodes in decreasing order of RSSI value from each part to ensure fewer errors will be brought in. However, sometimes there won't be such many candidate nodes to select. We use virtual users to simulate enough reference nodes. That it is utilizing the movement of sole users. In the following section, we will demonstrate the benefits of our algorithm using experiments.

IV. Performance Evaluation

A. Real World Experiments

In this section, we evaluate the performance of our proposed approach. We carry out experiments in a real environment, as shown in fig.3. The experiments are conducted in a 30 m × 30 m area. The area consists of indoor and outdoor parts. The indoor part is in a 15 m × 30 m area inside an academic building. The outdoor part is the rest of the area around the academic building. Due to limitations, we do not have 10 people with mobile devices in outdoor part at the same time. The experiments are conducted in the second scenario, that is, virtual localization. The experimental setup as follows: we select 10 fixed points in outdoor parts. The position of 10 fixed points can be obtained by GPS. These points are evenly distributed around the building. We also select 10 unknown points in indoor. The real position of 10 unknown points can be obtained by actual measurement. Because the position of 10 fixed points are known. By comparing with the results of the experiments, the error of OA-Loc can be obtained.

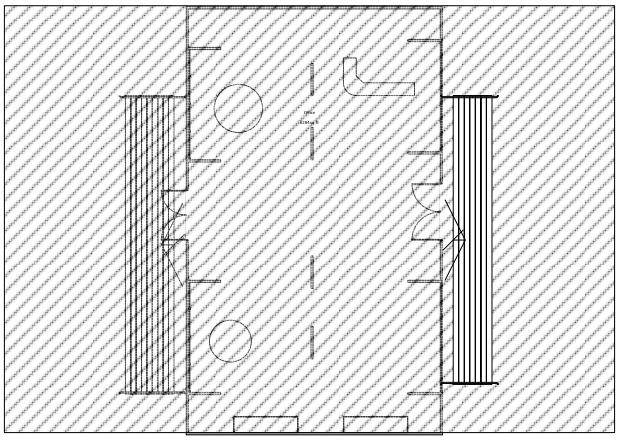

Figure3. A map of the area where the experiments were conducted.

B. The Constant g

The constant g is the most important parameter used in the algorithm described above. The impact of this parameter has been discussed in section III. In order to get the ideal value of the constant g in experimental environment, a range between 0.1 to 10 and an interval of 0.1 are used to test the parameter with 10 known points as reference points in outdoor part. The results are shown in fig.4. We can see that the ideal value for the experimental environment is 1.3. First the error decreases with the increasing of parameter g. Then they both increase quickly. As shown in fig.4, the average error of 10 unknown points is as minimal as 3 when parameter g is 1.3.

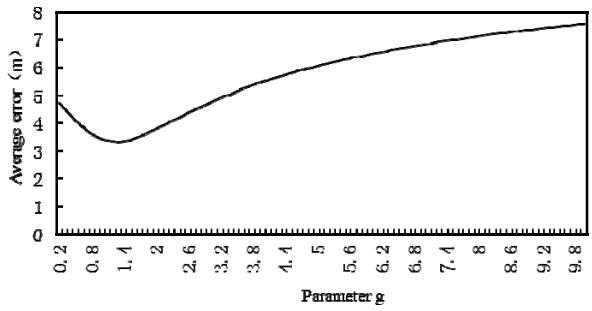

Figure4. Relation between parameter g and the error

C. Result and Analysis

In order to get the relationship between the error and the number of outdoor known points, and the distribution of outdoor known points, we chose 9, 7, 5, and 3 among 10 known points as reference points. In each case, there have nine different combinations of known points. And the constant g is 1.3. As shown in fig.5, the average error decreases with the increasing of the number of known points. However, when the number of known points is higher than a certain number, the average error does not increase significantly. As seen in fig.5, the case with 3 points compared with the case with 9 points, the average error of the latter is significantly less than the former. While the case with 7 points compared with the case with 9 points, their average error is relatively similar. It can also be seen from fig.5, different combinations of known points, or the distribution of points, will lead to different appearance of the average error.

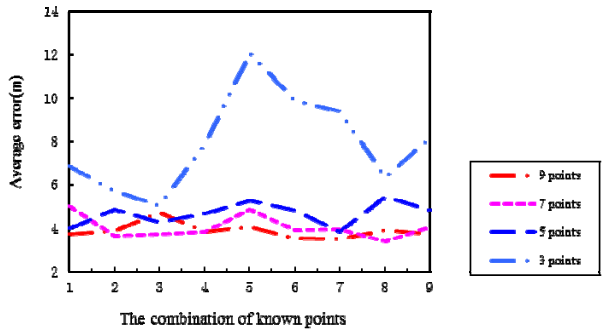

Figure5. The number of points, distribution and the error

In order to show the performance of OA-Loc visually, we mark the position and error of each unknown points in indoor when 10 known points in outdoor are deployed. The experimental results are shown in fig.6 and fig.7. Fig.6 shows the relative position between real position and the results of the experiments. Fig.7 shows the error of each unknown point which is located indoors. As it can be seen from two figures, the error of each point is different. This also shows that different distribution will lead to the different error. This is because the 10 known points are fixed and the distribution of unknown points for each unknown point is not the same. As shown in Figure, the average error is 3 m, while some points even at about 1 m.

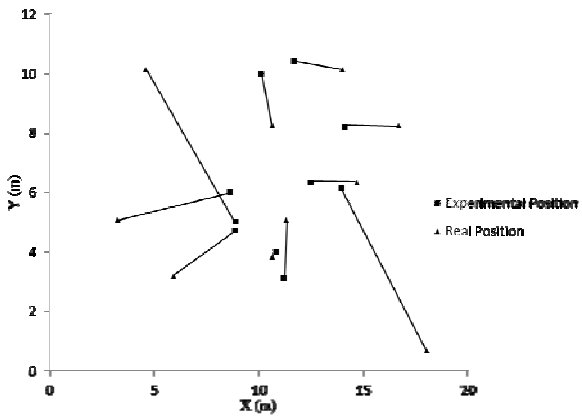

Figure6. The experimental v.s. real position of each point in indoor

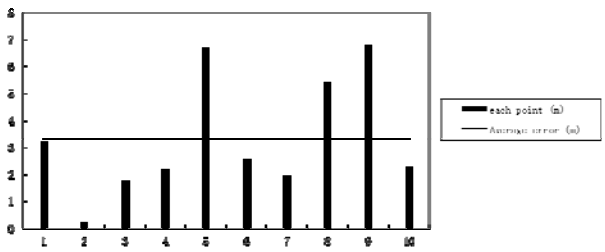

Figure7.The error of each point

V. CONCLUSION

In this paper, we mainly introduce a new idea to indoor localization and implement it. The method is based on

peer-to-peer architecture, where data is exchanged between mobile devices. The method can achieve a good performance by using Weighted Centroid Algorithm based on RSSI without any pre-deployed infrastructures although it has some limitations in practice. In the future, we can also use Bluetooth technology to replace Wi-Fi. The transmission power of Bluetooth is smaller, although it will lead to the decrease of the maximum transmission distance. And the power consumption of Bluetooth will be greatly reduced, which is very important for the resource constrained device.

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