Directional RSS-Based Localization for Multi-Robot Applications

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Abstract: This paper presents new techniques for simultaneous localization of multiple mobile robots using directional received signal strength (RSS). The RSS data is collected from the XBee wireless module with ZigBee technology. Directional RSS was achieved by a corner reflector antenna installed on the top of each mobile robot. The design parameters of the antenna were chosen by experiments and physical constraints of the robots. To map the RSS data to physical distance values, we first filtered the data using the well-known RANdom Sample Consensus (RANSAC) technique and then applied the least square regression method to further remove a large amount of outliers. In addition, real-time multi-robot localization and path planning are achieved by using an online statistical filter. The algorithm first identifies well-conditioned RSS values and sets a dynamic step size for trajectory generation. The online statistical filter was experimentally evaluated by comparing with two other algorithms, i.e., the Kalman and particle filters, and showed better performance than the other filters in terms of processing time. Preliminary evaluation on the directivity achieved by the corner reflector revealed that the mean orientation error of $-4.01°$.

Key–Words: Received signal strength (RSS), random sample consensus (RANSAC), multi-robot localization, antenna design, mobile robots

1 Introduction

Localization is one of the most challenging topic in the area of multi-robot systems and applications. An extensive amount of research has been conducted on outdoor navigation and localization using the Global Positioning System (GPS) [1, 2]. Research on indoor applications has somewhat lagged behind due to difficulties involved in wireless networking, pose measurements, and reliable data transmission [3].

Camera-based localization for both indoor and outdoor applications is one of the widely accepted methods for mobile robotic systems while its performance can be often sensitive to the camera characteristics (e.g., resolution and frame rate) and external factors (e.g., lighting and shadow) [4, 5]. In general, a high-speed processor is also required to handle onboard image processing. Ultrasound, infrared (IR) radio frequency identification (RFID) and radio-signal-based technologies (e.g., time difference of arrival (TDOA) and received signal strength (RSS)) have also been employed for indoor/outdoor localization of mobile robots. These technologies can provide a reliable communication range while requiring a much lower level of data processing than the camera-based approach. Ultrasound-based localization requires multiple pairs of ultrasonic emitters and receivers, as well as an additional RF (radio frequency), or equivalent, system in order to synchronize the receivers. Compared to the camera-based localization, this system can be easily implemented at a relatively low cost [6]. However, it also presents several limitations such as multi-path interferences, which may disturb the distance measurements between the emitter and receiver, and the exponentially increasing complexity when implemented in large scale [7].

IR-based systems are commonly found in commercial applications [8]. While IR cameras are less sensitive to external factors such as lighting or shadow when compared to regular cameras, it still requires line-of-sight in order to collect information for localization. In addition, IR proximity sensors usually work within a range of a meter that only allows short-distance localization. RFID tags and readers communicate via magnetic coupling and read the range between the tag and the reader. Passive tags, however, limit the reading range to less than 4 inches in general. Ultra high-frequency (UHF) RFID reader can extend the reading range up to 100 ft, but the modules are typically very expensive (e.g., \$500-2000 per module). Regarding the radio signal based localization, some studies reveal that TDOA shows better sensing range and resolution characteristics than RSS [9].

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However, it usually uses a sound source for measuring the TDOA and therefore can be more susceptible to environmental barriers than a radio signal. TDOA may use a radio signal source instead of sound while requiring additional hardware implementation to enable high-speed data processing.

RSS-based localization techniques are well-suited for multiple mobile robot applications due to their simplicity, easy identification of multiple robots, and communication and distance sensing capabilities. There still exist several technical challenges: i) noisy raw RSS data and inconsistent radiation patterns; ii) nonlinearity between RSS data and physical distance values; iii) low signal transmission power limiting the range of distance measurements; iv) difficulty in simultaneous mobile localization; and v) no information on orientation. In an attempt to address these challenges, several filtration techniques, such as a particle filter [10] or an extended Kalman filter (EKF) [11], have been applied to smoothen the noisy RSS data. Distance-only measurements often requires an additional algorithm, such as triangulation, to estimate the position [12]. Range-only SLAM (Simultaneous localization and mapping) can perform position estimation without such additional algorithm [13]. To obtain the orientation in addition to the distance, the system may utilize additional hardware such as magnetic landmarks for magnetic field based global localization [14]. Range-only SLAM may utilize an odometry sensor, such as a camera, or kinematics of a mobile robot to detect orientation.

In terms of inconsistent radiation patterns, reflectors are widely employed to modify the radiation patterns or increase RSS for low-power radio localization [15, 16, 17]. A recent study investigated the accuracy of RSS-based indoor localization by identifying the channel parameters by applying linear regression [18]. In addition, the Signal-Index-Pair method was proposed to preprocess the data to enhance the precision of the NN (Neural Network) locating model [19]. Graefenstein et al. [15] proposed a system that maps RSS to distance and direction measurements with improved localization performance compared to the direction-only techniques. The system achieved improved directivity of the radiation pattern by adding a simple aluminum metal plate as a reflector antenna. In terms of the antenna reflector design, a parabolic reflector with rotational actuator is employed and experimentally evaluated to estimate direction of arrival (DoA) of radio signal [17]. However, no extensive research has been conducted in the area of the antenna reflector design for RSS-based localization of networked mobile robots.

This paper presents a localization method for multiple mobile robots using filtered directional RSS as illustrated in Fig. 1. Antennas are designed to increase directivity of the radiated signal patterns, but have been minimally used for RSS-based localization. In our system, however, a single corner reflector is designed to better estimate the relative orientation of the target. For the collected raw RSS data, robust parameter estimation is conducted using a well-known path loss model [20] for distance measurements. The RANdom Sample Consensus (RANSAC) method is first applied to filter out outliers in the data. Selected inliers are then fitted into a least square model. Simultaneous localization involves two steps: i) real-time data filtration to identify well-conditioned RSS data for pose (position and orientation) estimation; and ii) path planning between the tracker and the target. The Kalman or particle filter is frequently used for noise cancellation to solve this specific problem [21, 22]. However, these filters require processing time for predicting and correcting the data. To reduce the computational costs, a simple statistical filter is proposed in this paper and its processing time is evaluated by comparing with the methods using the Kalman filter and the particle filter.

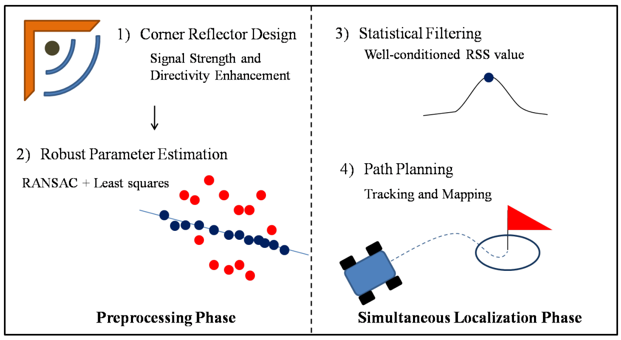

Figure 1: Localization is realized by 1) improving the signal strength and directivity by adding a corner reflector; 2) estimating the parameters; 3) identifying well-conditioned RSS data; and then 4) controlling the robot to locate the stationary/mobile target.

2 Signal Reflector Design

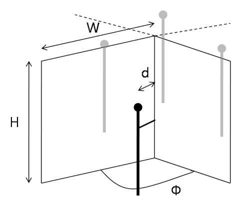

Figure 2: A corner reflector with a dipole located in between two plates

2.1 Infinite-sized corner reflectors

Among various reflector candidates, a corner reflector is considered due to its simplicity in design and large azimuth response width compared to a flat or parabolic reflector [23]. Assuming that the robots move horizontally on a flat surface propagating the signal in the azimuth angle, a corner reflector is sufficient to receive the signal along the azimuth direction.

A general design of the corner reflector contains a dipole antenna located between the two infinite-sized flat plates which limits the radiation patterns. The angle between the two plates may vary, but we selected 90° to ensure maximum directivity while maintaining the communication range. Although a smaller angle would provide better directivity, it limits the communication range significantly [24]. When the angle between the two plates are fixed at 90°, the maximum directivity ($\rho_{\max}$) is found at the half of the given RF-module's wavelength [24].

2.2 Directivity vs. reflector size

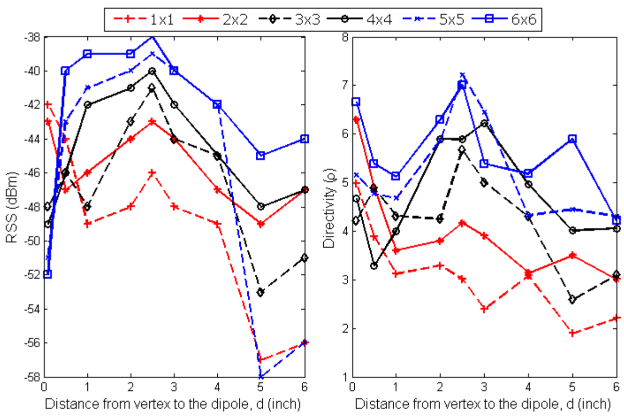

Figure 3: Experimental results of RSS and directivity ρ versus d, measured at $D = 36$ [in] (distance from the target)

It is physically impossible to build an infinite-sized antenna. For multi-robot applications, it can be further constrained by the physical size of the robot in order for not to interfere the robots' trajectories. To observe the changes in signal directivity due to the size of the corner reflector and the location of the dipole, six different sizes were tested experimentally for varying d (distance from the corner to the dipole): $(1\times1), (2\times2), \cdots, (6\times6)$ [in^2]. Fig. 3 shows RSS values and ρ (directivity) versus d for six selected finite-sized reflectors using a 2.4 GHz RF-module with 5 [in] of wavelength. Higher RSS and ρ values were observed for larger reflectors. More specifically, the maximum radiation intensity was found around $d = 2.5$ [in] for the reflectors larger than (2×2) complying with the infinite-size antenna model described in [24]. On the other hand, the smaller reflectors showed that $\rho_{\max}$ is near the vertex. This may be resulted by diffracted signals captured by the dipole near the corner. Moreover, the signals are hardly blocked on the other side of the reflector causing a lower directivity and RSS for the smaller reflectors.

2.3 Mobile platform with a corner reflector

Fig. 4 shows the mobile platform where the developed RSS-based localization techniques are implemented. The robot is about 3 inches (in) along each dimension. This mobile robot is equipped with a differential drive system, an onboard microprocessor (ATmega328), a magnetometer, batteries (7.4V lithium polymer), and an XBee wireless module with ZigBee network technology. The quadrature encoder provides a resolution of 48 counts per revolution which corresponds to a linear resolution of slightly under 3mm. The magnetometer (HMC5883L, Honeywell) measures the direction of the magnetic field, providing digital values through the I2C interface, so that the robot can recognize its absolute orientation. In indoor environments, the magnetometer does not provide an accurate orientation as the magnetic field is often distorted. However, it can sufficiently provide low-resolution angles, for example 45° of rotation.

The robot contains two DC gear motors installed for driving the system and enabling the tracked wheels 360° of rotation without translational motion. While a larger reflector seems to achieve a better directivity and detection range, the size of the physical robot shown in Fig. 4 is about $3\times3\times3$ which constrains the distance between the two outer edges of the plates to 3 [in] in order not to exceed the size of the robot. Therefore, we selected $W = H = 2$ and located the dipole near the corner, where $d = 0.1$ [in], which showed sufficiently high values of RSS and ρ as shown in Fig. 3.

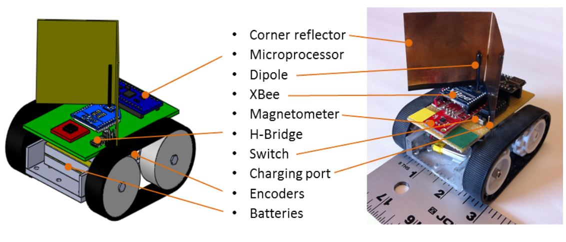

Figure 4: CAD drawing (left) and physical prototype of the mobile robot (right).

3 RSS to Distance Mapping

3.1 Log-distance path loss model

The RSS measurement quantifies the received power of wireless packets sent via the IEEE 802.15.4 protocol. In the real (free space) case, this value varies inversely with the square of the distance and therefore has been suggested as a means to estimate distances between nodes in mobile sensor networks [9, 25]. In

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order to map the RSS values to the distance measures, we adopt the indoor propagation model based on the log-distance path loss model given by [20]

$$L = L_0 + 10\gamma \log_{10}\left(\frac{D}{D_0}\right) + X_g \qquad (1)$$

where L_0 is the pass loss at the distance D_0 measured in decibel (dB), γ is the path loss exponent, and X_g is a Gaussian random variable with zero mean and a standard deviation, σ.

Fig. 5 (left) shows the mean RSS values of 10 samples measured at each distance between 2 to 130 [in] where the bar length indicates the standard deviation. The standard deviation tends to increase as the distance becomes farther. Also, the RSS measurements decreases monotonically until about 84 [in] and starts to slow down afterwards. Fig. 5 (right) shows that the RSS data is linearly dependent to the $\log_{10}$-distance up to $10^{1.7} \sim 10^{1.8}$, corresponding to $50 \sim 63$ [in]. Therefore, we consider the reliable range of robot-to-robot distance measurements is up to 60 [in], where it follows the $\log_{10}$-distance path loss model in Eq. (1). The estimated parameters for this range are computed by $L_0 = -19.96$ dB, $\gamma = -2.14$, and $d_0 = 2$.

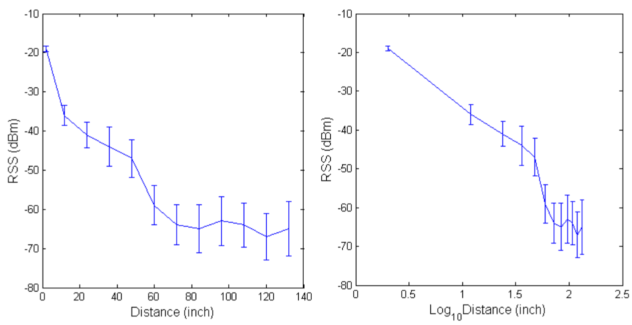

Figure 5: RSS vs. distance measurements (left) and $\log_{10}$-distance (right)

3.2 RANSAC with least sqaure regressions

One of the major advantages of using RSS for distance sensing is that it is already built in most radios and therefore requires no additional sensing hardware. However, recent work has showed that the inherent inaccuracies of using RSS in practical environments makes it almost useless for distance sensing without significant preprocessing or computational resources [25, 26]. RSS data typically involves a large amount of outliers and therefore the data preprocessed through the linear regression can only fall into a bad fit. To address this problem, we first applied RANSAC [27] which is an iterative method to estimate model parameters from a set of observations containing outliers. A subset of measurements is randomly sampled, its average is computed, and finally all the other measurements are tested against this average value. If measurements fit well to the average, they are added to the subset and rejected otherwise. To further remove the outliers, we applied the least square method to the RANSAC filtered data. Fig. 6 shows the RSS data processed by the RANSAC and least square regression methods.

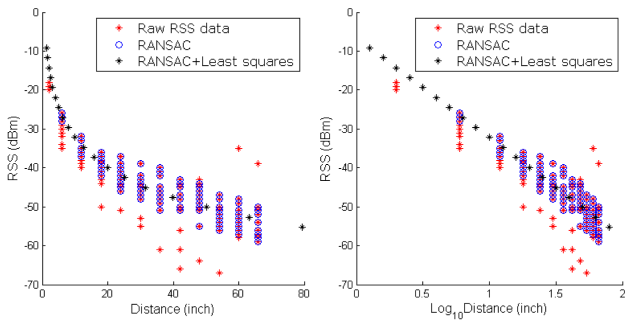

Figure 6: Inliers extraction from raw RSS data versus distance (left) and $\log_{10}$-distance (right)

4 Online Filter and Path Planning

4.1 Online statistical RSS filter

For multiple mobile robot applications, online RSS data processing and path planning using the processed data are essential. While there exist several well-known algorithms, such as the Kalman and particle filters, that are proven to handle noisy measurement data, these filters still require the data training process which may not be desirable for real-time, embedded applications.

To reduce computational costs, we developed a simple, yet effective, online filtering algorithm based on accumulated statistical data. This filter determines well-conditioned RSS measurements for estimating the target distance. The filtered RSS data is considered well conditioned if the sampled data forms a Gaussian distribution. A previous work showed that RSS data is non-Gaussian [28]. However, by adding the corner reflector, our experiments showed that directional RSS data exhibit a Gaussian distribution in a near field (less than 60 [in]). A non-Gaussian distribution is observed when two RF-modules are apart from each other by more than 60 [in], or when there is no corner reflector. The second case is obvious since the radiation pattern is not symmetric.

The 'GET RSS' function shown in Algorithm 1 achieves well-conditioned RSS values by comparing them with the mean-median-mode statistic metric. Consecutive RSS values satisfy the normality if

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the mean, median and mode values are the same. To be comparable with the RSS values given by integers, the mean value is also rounded to a nearest integer. It also eliminates the outliers if the values are not in $\pm 2\sigma$ (95% confidence interval), where σ is the standard deviation.

Algorithm 1 Online RSS filter

procedure GET RSS(rss)
  $\hat{X} = sort(X); X_{sd} = std(\hat{X})$
  $X_{mean} = round(mean(\hat{X}))$
  $X_{median} = round(median(\hat{X}))$
  $X_{mode} = round(mode(\hat{X}))$
  if $X_{mean} = X_{median} = X_{mode}$ **then**
    $RSS = X_{mean}$
  else
    if $rss - 2X_{sd} \leq rss \leq rss + 2X_{sd}$ **then**
      $X \leftarrow rss$
    end if
  end if
  return RSS
end procedure

4.2 Online path planning

Algorithm 2 estimates the target distance by mapping the RSS values into the euclidean or $\log_{10}$ distance. If the estimated distance is less than D_a, the shortest distance threshold, the robot stops and waits for the next task. Otherwise, the robot first scans RSS around itself by rotating 360° for orienting the target. As the corner reflector provides a significant RSS change every 45° rotations, initial scanning is conducted at every 45°. Once the robot collects eight measurements, it returns to the orientation where $RSS_{\max}$ was obtained. The robot then moves forward with the step distance, $D(RSS)$, defined by

$$D(RSS) = 2 \cdot \alpha \cdot 10^{-(RSS+19.96)/21.4} \quad (2)$$

where α is the ratio of the step distance to the estimated distance. The step size is a function of RSS, i.e. a longer step distance when the target is far away and a shorter step distance when the target is close. Constant values were determined by replacing L in (1) with D. A smaller value of α results in a smaller $D(RSS)$. That means, the robot will take a greater number of steps to reach the target. On the other hand, a large α indicates a large $D(RSS)$ implying that the robot will move a rather large distance in a single step, proportional to the exponential of RSS. In any case, the robot will converge to the target as $D(RSS)$ would be fairly small near the agent. To find the optimal value of α (0.2, 0.4, 0.6, and 0.8), we ran 10 simulations for different values of α. The results showed that the minimum number of steps were required to reach the target when $\alpha = 0.4$. This simulation does not take account the step time, therefore it may not necessarily reflect the time efficiency. However, experimental results measuring the total time for reaching the target were highly correlated with the computed number of steps (r=0.948, $p<0.05$).

Algorithm 2 Target Tracking

if $D(RSS) < D_a$ **then** *Break*
else
  for $i = 1$ to 8 **do**
    Rotate 45°
    $RSS[i] \leftarrow$ Get RSS
  end for
  $RSS_{max} = max(RSS)$
  for $i = 1$ to 8 **do**
    Rotate 45 °
    if Get RSS $\geq RSS_{max}$ **then**
      Move Forward with $D(RSS)$
      Break
    end if
  end for
end if

5 Preliminary Evaluation

The developed algorithms were implemented in four mobile robots (Fig. 4) and tested for the following experimental scenarios: 1) three robots tracking a single mobile target, and 2) a single robot localizing three stationary targets for mapping. Performance of the proposed online statistical filter was evaluated by comparing the task completion time with the Kalman and particle filters as they are well-known leading filters in wireless sensor networks [29]. We also tested the effectiveness of the corner reflector for localizing the target by evaluating moving directions towards the target at each step.

5.1 Evaluation of the online statistical filter

We have conducted experiments to validate the statistical online filtering algorithm by analyzing the tracking time for different distances and comparing the results with the Kalman and particle filters. 10 to 60 inches of distance between the robot to the target were considered and, for every 10 inches, tracking times were repeatedly measured for 10 times and averaged. As shown in Fig. 7, the proposed online statistical filter shows the shortest time to locate the target among the three filters. The particle filter was somewhat better than the Kalman filter, but both of them took significantly more time than the new statistical

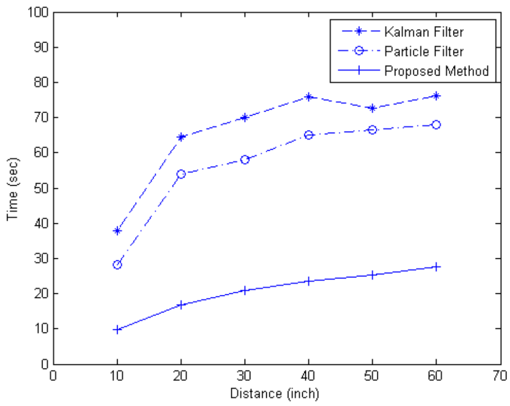

Figure 7: Tracking time [sec] vs. distance [in]: 10 experiments are conducted at each distance for Kalman filter, particle filter, and proposed statistical online filter.

filter. For the Kalman filter, process noise and observation noise models were tuned at $w_k \sim N(0, Q_k)$ and $v_k \sim N(0, R_k)$, where covariance $Q_k = 0.01$ and $R_k = 0.08$. In general, a particle filter requires a large set of particles, but when the number of particles increases, the system showed low-speed as we use low-speed microprocessor. In our test, 16 particles showed successful tracking with minimal particles. Fig. 7 shows trajectories of mobile robot moved from the left to the right repeatedly for 20 times and its orientation histogram toward the agent. The mean orientation error was about -4.01° while the interim trajectories were also limited by $< |\pm 45|^\circ$ as anticipated by the properties of the corner reflector.

5.2 Fixed and mobile target localization

The presented algorithms were embedded in four identical (but with different roles assigned) mobile robots. First, three robots communicate with and track a single mobile target. Second, a single mobile robot locates three stationary targets by visiting one after one. Fig. 8 (a) and (b) show experimental snapshots. Among 10 trials in total, it showed a 80% success ratio for the first scenario. Two trials were stopped due to collision among the robots. The second scenario demonstrated sequentially visiting the three targets successfully for all 10 trials. During the experiments, signal obstruction was observed when the mobile robots are lined up toward the target. Although the robot eventually tracked the target, it took additional time for reaching the target.

6 Conclusion

This paper presented a directional RSS-based technique for multiple mobile robot localization. Adding

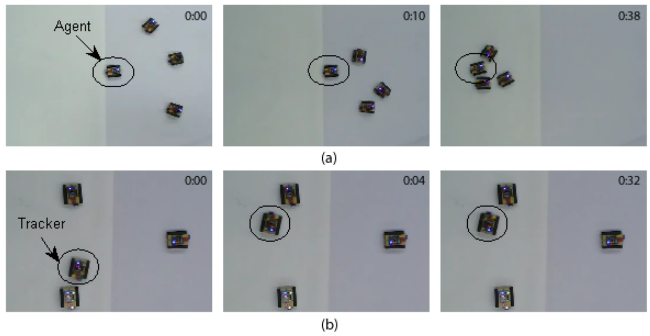

Figure 8: (a) Three mobile robots track the moving agent; (b) Single tracker reaches each agent sequentially.

a simple corner reflector to the antenna realized reliable detection of relative target orientation. Our experiments conducted for selecting the design parameters of the corner reflector can be easily replicated by others who wish to design their own corner reflector for a specific application to achieve the desired sensing range and directivity. The developed data processing algorithms, including RANSAC combined with the least square regression method and the online statistical filter, ensure the quality of the data by effectively eliminating outliers and selecting well-conditioned data for online processing. The presented path planning for the mobile robots utilizes a dynamic step size determined by the RSS values in which the robot makes a longer movement when it is far from the target and make smaller steps when it is near the target. Different strategies may replace the current path planning scheme once fully investigated and compared across different techniques. In addition, obstacle avoidance and collision-free trajectory generation are important areas of exploration to fully realize the effective multirobot localization and path planning.

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