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A Multi-source Fused Location Estimation Method for UAV Based on Machine Vision and Strapdown Inertial Navigation

Jiapeng Li[1], Shuo Shi[1,2](✉), and Xuemai Gu[1,3]

[1] School of Electronic and Information Engineering, Harbin Institute of Technology, Harbin, Heilongjiang 150001, China
lijiapeng_atlantis@163.com, crcss@hit.edu.cn
[2] Network Communication Research Centre, Peng Cheng Laboratory, Shenzhen, Guangdong 518052, China
[3] International Innovation Institute of HIT in Huizhou, Huizhou, Guangdong 516000, China

Abstract. In recent years, unmanned aerial vehicle (UAV) technology has been widely used in industry, agriculture, military and other fields, and its positioning problem has been a research hotspot in this field. To solve the problem of invalidation of integrated navigation of global positioning system (GPS) and strapdown inertial navigation system (SINS) in indoor and other areas, this paper presents a multi-source information fusion location algorithm based on machine vision positioning and SINS. Based on image coordinate system (ICS), body coordinate system (BCS) and navigation coordinate system (NCS), combined with AprilTags recognition and positioning technology, this paper builds NCS with AprilTags array to get the position observation of UAV. Based on the idea of multi-source information fusion, this paper applied third-order fused complementary filter algorithm, which combines with the SINS to obtain accurate three-axis speed and position estimation. Finally, the reliability is verified by the test of the UAV experimental platform.

Keywords: Unmanned aerial vehicle · Strapdown inertial navigation system · Multi-Source information fusion

1 Introduction

As a new member of small Unmanned Aerial Vehicles (UAVs), quad-rotor UAVs have many advantages, such as small size, flexible flight, vertical takeoff and landing, hovering at fixed points, and portability. It has been widely used in military surveillance, disaster prediction, agricultural mapping and civil life, and has gradually become a hot topic for researchers and scholars.

A stable control and execution system is a prerequisite for the normal operation of an unmanned aerial vehicle. Accurate, low-latency, low-noise estimation for attitude, speed and position are necessary for the normal operation of the controller. So far, no sensor has been able to measure the flight attitude, speed and position of an UAV at anytime and anywhere with precision and no delay in the navigation coordinate system.

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There are many sensors that can be used to estimate the flight status of an UAV, but they have different working principles, measuring objects, working conditions and data delays. Therefore, it is difficult to estimate the flight status of an UAV accurately, with low delay and low noise through a single sensor or through multiple sensors without any processing.

In recent years, the concept of multi-source information fusion has been proposed, and the location method for UAV based on this concept has gradually become a research hotspot in this filed. Based on an inertial measurement unit (IMU) consisting of a three-axis gyroscope and accelerometer [1], as well as an array of magnetic angular rate and gravity (MARG) sensors including a three-axis magnetometer, the direction of gyroscope measurement error is calculated as a quaternion derivative, and accelerometer and magnetometer data are allowed to be used to analyze. Therefore, reliable estimation of UAV flight attitude can be achieved. The strapdown inertial navigation system has periodic oscillation error in pure inertial navigation mode, which seriously affects the navigation accuracy. In [2], according to the principle of equivalence, the external horizontal damping network of SINS is designed, and the periodic oscillation is suppressed by the difference between the velocity of the system itself and the velocity of the electromagnetic log, which improves the accuracy of the system.

It is difficult to achieve accurate and reliable state estimation by IMU alone. In [3], the accuracy of the airborne GPS in a static environment is evaluated and its availability in low-cost projects is demonstrated. The combination of GPS and strapdown inertial navigation is a feasible method for state estimation. However, the update frequency of GPS is much lower than that of SINS. The two streams are out of sync, which affects navigation accuracy. In [4], a digital high-pass filter is used to pre-filter the measured signal and to filter the Schuler period of the difference between SINS and GPS discrete velocity, which greatly improves the navigation accuracy. At present, the common method of SINS/GPS integrated navigation system is based on ground speed, which has some limitations and is interfered by abnormal measurements. In [5], a dynamic coarse alignment method for SINS/GPS integrated system based on location track is presented, which is proved to be more robust than the current popular methods through simulation and measurement. Aiming at the integration of SINS with GPS and the possible violation of Gaussian assumption of process noise [6], a new process uncertainty robust Student's t-based Kalman filter for process uncertainty is presented, and its robustness in suppressing process uncertainty is proved.

However, in many cases, GPS does not work properly, and SINS requires other location observation sensors to participate in multisource information fusion. By calculating the time difference of arrival (TDOA) of the transmitted signal [7], a new positioning method based on multipoint positioning is proposed to replace the GPS positioning method. In [8], a colored noise model is proposed using the received signal strength (RSS) by the onboard communication module and applied to the extended Kalman filter (EKF) for distance estimation. In [9], a particle swarm optimization algorithm is proposed for wireless self-organizing sensor networks. The UAV location search model is described as a constrained optimization problem of a multi-objective utility function to dynamically obtain the optimal location of multi-UAVs.

Machine vision-based indoor positioning of robots, including UAV positioning, is also a hot research direction. The abundant parallel lines and corner points on the ceiling can be used as visual positioning features for indoor mobile robots. In [10], based on the natural characteristics of the ceiling, a new visual positioning method is proposed, and its validity is verified by error analysis and experiments. Redundant navigation systems are essential for the safe operation of UAVs in high-risk environments. In [11], a visual-based path tracking system is proposed for the autonomous and safe return of UAVs under major navigation failures such as GPS interference.

Based on the above observation, this paper aims to designing an indoor navigation algorithm for UAV based on multi-source information fusion of machine vision positioning and strapdown inertial navigation. Specifically, the focus of this study includes:

i. Based on the ground positioning tag array and the flight attitude of the UAV, a real-time positioning method based on the onboard visual unit is constructed, and the estimation of yaw is further corrected.
ii. Visual localization has some problems, such as slow update rate, high delay, easy mutation and failure. Combining strapdown inertial navigation with advantages of low latency, high update rate and long-time stability, an optimal estimation of the UAV's attitude, speed and position can be obtained by means of multi-source information fusion. The effectiveness of the method is proved by the actual measurement.

2 Inertial Navigation

Strapdown inertial navigation requires a mathematical platform coordinate system constructed from the flight attitude angle of the UAV, and then the platform inertial navigation estimation is performed. SINS is built on the body coordinate system (BCS) and navigation coordinate system (NCS). The rotation matrix R_b^n describes the process that the coordinate of a point changing from BCS to NCS. Defining pitch (θ), roll (γ) and yaw (ψ) as the angles of rotation about X, Y, Z axes, we can obtain R_b^n and R_n^b as follows:

$$R_b^n = \begin{bmatrix} \cos\gamma\cos\psi & \sin\theta\sin\gamma\cos\psi - \cos\theta\sin\psi & \cos\theta\sin\gamma\cos\psi + \sin\theta\sin\psi \\ \cos\gamma\sin\psi & \sin\theta\sin\gamma\sin\psi + \cos\theta\cos\psi & \cos\theta\sin\gamma\sin\psi - \sin\theta\cos\psi \\ -\sin\gamma & \sin\theta\cos\gamma & \cos\theta\cos\gamma \end{bmatrix} \tag{1}$$

$$R_n^b = \left(R_b^n\right)^T = \left(R_b^n\right)^{-1} \tag{2}$$

The acceleration vector measured by the onboard IMU is rotated to NCS by a fictitious mathematical coordinate system. The acceleration of the body motion is expressed on NCS by platform inertial navigation, and then the speed and position estimation of the UAV is obtained by integrating as follows:

$$a_{vn} = \left(\lambda_R + R_b^n\right)\left(a_{mb} + \lambda_m\right) - \lambda_g g_n \tag{3}$$

$$\ddot{s}_n = \dot{v}_n = a_{vn} \tag{4}$$

Where a_{vn} denotes motion acceleration vector in NCS, a_{mb} denotes measuring acceleration vector in BCS, g_n denotes gravity acceleration vector in NCS, λ_R denotes the error component relative to real rotation matrix, λ_m denotes the measurement error of IMU, λ_g denotes rate of variation of gravity acceleration with height, s_n and v_n respectively denote speed and position in NCS.

It can be seen from (3) that although SINS can provide three-axis speed and position estimation during the flight of an UAV, it is difficult to conform to the real results due to various errors and interference.

3 Visual Orientation

AprilTags is a visual reference library, which can quickly realize 3D positioning and inclination measurement (see Fig. 1), and is widely used in robot positioning technology. Considering the power consumption and load-carrying capacity of small UAVs, this paper creates an AprilTags visual localization algorithm based on monocular vision and AprilTags array.

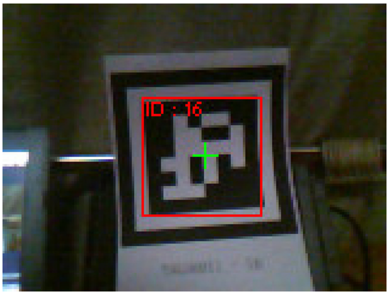

Fig. 1. AprilTags location and recognition

3.1 AprilTags Location Algorithm

AprilTags identification and positioning system [12] is mainly composed of tag detector and coding system. The tag detector is used to locate the tag and detect the tilt angle. The encoding system is used to extract the information contained in the tag.

AprilTags recognition and positioning is mainly done in three steps [13]. Firstly, calculate the gradient of each pixel and further detect the segments in the image. Secondly, a depth-first search method based on depth 4 is used to find quadrilateral in the image. Compare the standard libraries to determine if tags exist in the quadrilateral and the ID of the tag. Thirdly, the isotropic matrix is calculated by direct linear transformation [14], and the relative position and rotation angle between the label and the camera are calculated.

3.2 AprilTags Array Location Algorithm

In this paper, several AprilTags are arranged into a two-dimensional array at regular equal distances (see Fig. 2). According to the tag position and ID number in the field of view, as well as the UAV attitude angle, the relative position relationship is constructed (see Fig. 3).

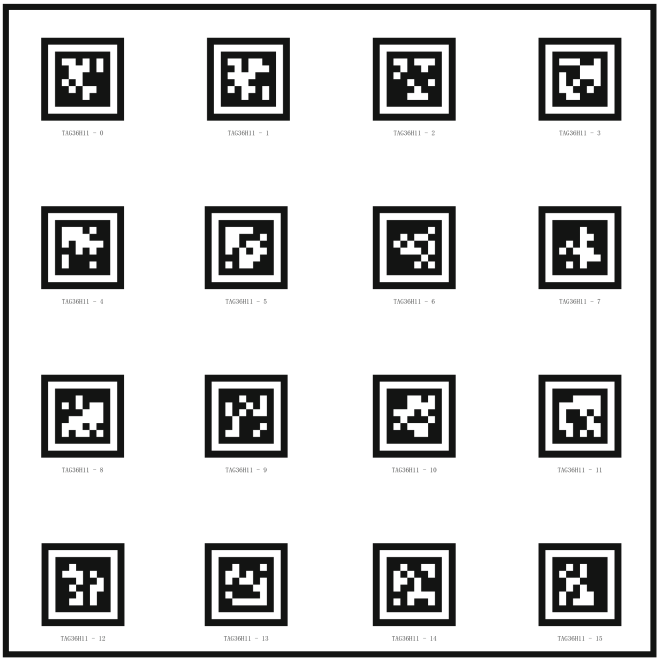

Fig. 2. AprilTags array

In Fig. 3, $OXYZ_s$ denotes horizontal body coordinate system (HBCS), $OXYZ_b$ denotes BCS, α denotes the AprilTags array plane, β denotes the image plane with Z axis of BCS as normal, T denotes the center of the identified AprilTag, A denotes the projection of camera normal on β, B denotes the projection of UAV on α. The position deviation between tag center and image center can be represented by orthogonal T_iC and CA.

Assuming that the angle between vector $\vec{O}C$ and vector $\vec{O}P$ is θ_T, the angle between vector $\vec{O}C$ and vector $\vec{O}T$ is γ_T, and the positive direction of rotation is defined by the right-handed helix rule, the relationship can be obtained as below:

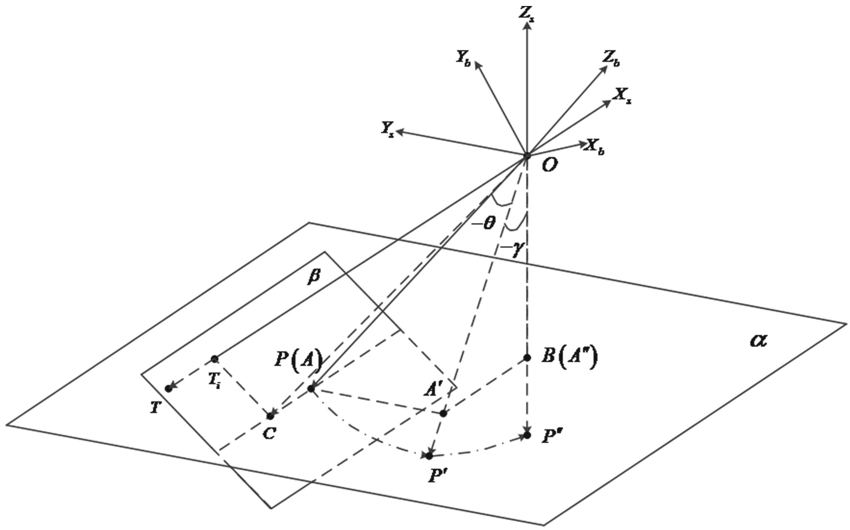

Fig. 3. Image coordinate conversion algorithm

$$\frac{\vec{O}\,T}{\left|\vec{O}\,T\right|_b} = R_{x,b}\left(\delta\left|\vec{C}\,P\right|\right)R_{y,b}\left(\delta\left|\vec{T_i}\,C\right|\right)\frac{\vec{O}\,P}{\left|\vec{O}\,P\right|_b} = R_{x,b}(\theta_T)R_{y,b}(\gamma_T)\frac{\vec{O}\,P}{\left|\vec{O}\,P\right|_b} \tag{5}$$

where δ is a constant greater than zero, which is determined by the camera resolution and viewing angle. Vector $\vec{O}\,T$ can be expressed as below:

$$\frac{\vec{O}\,T}{\left|\vec{O}\,T\right|_b} = R_{x,b}(\theta_T)R_{y,b}(\gamma_T)\begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} -\sin\gamma_T \\ \sin\theta_T\cos\gamma_T \\ -\cos\theta_T\cos\gamma_T \end{bmatrix} \tag{6}$$

Vector $\vec{O}\,T$ and $\vec{O}\,B$ can be expressed respectively as follows:

$$\frac{\vec{O}\,T}{\left|\vec{O}\,T\right|_s} = R_{z,s}(\psi)R_{y,s}(\gamma)R_{x,s}(\theta)\frac{\vec{O}\,T}{\left|\vec{O}\,T\right|_b} \tag{7}$$

$$\frac{\vec{O}\,B}{\left|\vec{O}\,B\right|_s} = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \tag{8}$$

Vector $\vec{O}\,B$ points to the negative direction of z-axis of HBCS. Its mode length is measured directly by the laser ranging module of the UAV, which is denoted as d.

The mode length of vector $\vec{O}B$ can be obtained by converting a simple trigonometric function as follows:

$$\left|\vec{O}B\right| = \left|\vec{O}P\right| \cos\theta\cos\gamma = d\cos\theta\cos\gamma \tag{9}$$

$$\vec{O}B_s = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \left|\vec{O}B\right| = \begin{bmatrix} 0 \\ 0 \\ -d\cos\theta\cos\gamma \end{bmatrix} \tag{10}$$

Vector $\vec{O}T$ and vector $\vec{O}B$ have the same z-axis component, so we can obtain the representation of vector $\vec{O}T$ in HBCS as below:

$$\vec{O}T_s = \begin{bmatrix} t_{x,s} \\ t_{y,s} \\ t_{z,s} \end{bmatrix} = \begin{bmatrix} t_{x,s} \\ t_{y,s} \\ -d\cos\theta\cos\gamma \end{bmatrix} \tag{11}$$

Assuming that the actual coordinate of point T in the array is $T_\alpha\left(t_{x,n}, t_{y,n}, 0\right)$, then the coordinate of point B in the array can be expressed as $B_\alpha\left(t_{x,n} - t_{x,s}, t_{y,n} - t_{y,s}, 0\right)$, and the position of the UAV can be obtained as below:

$$\vec{p}_n = \begin{bmatrix} t_{x,n} - t_{x,s} \\ t_{y,n} - t_{y,s} \\ d\cos\theta\cos\gamma \end{bmatrix} \tag{12}$$

4 Multi-source Information Fusion

4.1 Heading Direction Estimation

To ensure that the NCS defined by SINS is consistent with that defined by the AprilTags array, the heading angle of the UAV needs to be corrected by the rotation angle of AprilTags. In this paper, the error of two angles is used as compensation, the heading angle is corrected, and the estimation is obtained, which ensures the complete synchronization of the two NCS. The fusion estimation method is shown below:

$$\hat{\psi}(k) = \hat{\psi}(k-1) + \mu e(k) \tag{13}$$

$$e(k) = \begin{cases} e_1(k) \\ e_2(k) \\ e_3(k) \end{cases} = \begin{cases} \psi_m(k) - \psi(k-1) & , min\{abs[e(k)]\} = abs[e_1(k)] \\ \psi_m(k) - \psi(k-1) + 360 & , min\{abs[e(k)]\} = abs[e_2(k)] \\ \psi_m(k) - \psi(k-1) - 360 & , min\{abs[e(k)]\} = abs[e_3(k)] \end{cases} \tag{14}$$

where μ denotes a constant between 0 and 1 as correction rate, $e(k)$ denotes the error of two heading angles.

4.2 Velocity and Position Estimation

Velocity and position estimation of UAV obtained from SINS has the advantage of low delay, but it is difficult to directly apply to control system because of measurement error and interference. The location estimation of UAV obtained by the machine vision location algorithm proposed in Sect. 3 has the advantages of high delay and poor stability, and it is also difficult to apply directly to the control system. To solve this problem, third-order fused complementary filter algorithm is applied (see Fig. 4), which can get reliable speed and location estimates by complementing each other.

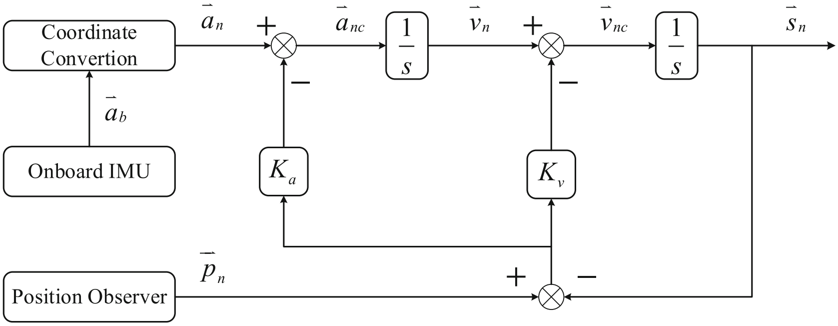

Fig. 4. Third-order fused complementary filter algorithm

In Fig. 4, $\vec{a}_n$ denotes the motion acceleration in NCS from SINS, $\vec{p}_n$ denotes the position estimation from location algorithm proposed in Sect. 3. The discrete iteration of this algorithm can be represented as follows:

$$a_n(k) = a_{vn}(k) + K_a(p_n(k) - s_n(k)) \tag{15}$$

$$v_n(k) = v_n(k-1) + a_n(k-1)T + K_v(p_n(k) - s_n(k)) \tag{16}$$

$$s_n(k) = s_n(k-1) + v_n(k-1)T + \frac{1}{2}a_n(k-1)T^2 \tag{17}$$

where T denotes the iteration period of the algorithm, $a_{vn}(k)$ denotes the motion acceleration in NCS at time k, $a_n(k)$, $v_n(k)$ and $s_n(k)$ respectively denote the estimation of acceleration, velocity and position of multi-source information fusion algorithm, K_a and K_v are both compensation factors (Fig. 5).

5 Experimental Testing

In this chapter, a planar array consisting of 16 AprilTags is designed according to the rules of Chapter 3. The positioning algorithm proposed in this paper is tested by a self-developed four-rotor UAV experimental platform, and the test results are actually sampled (see Fig. 7).

Since all three axes are visually located to obtain position estimates, this result can represent the X and Z axes. We can see in Fig. 7, Fig. 8 and Fig. 9 that location estimation after multi-source information fusion has faster response speed and almost the same positioning accuracy than machine vision location estimation. This is sufficient to demonstrate the reliability of the algorithm presented in this paper (Fig. 6).

Fig. 5. Self-developed four-rotor UAV test platform

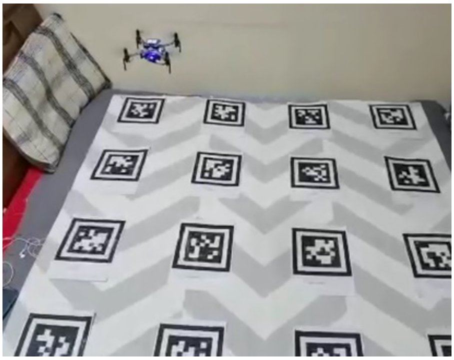

Fig. 6. UAV hovering in the AprilTags array area

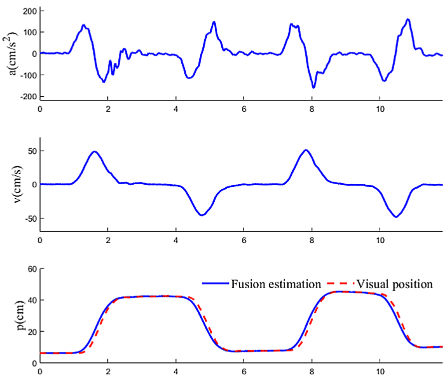

Fig. 7. Estimation of motion acceleration, velocity and position of x-axis

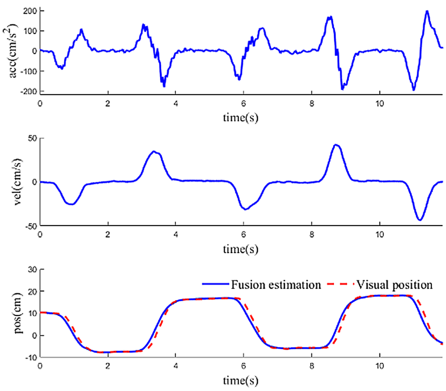

Fig. 8. Estimation of motion acceleration, velocity and position of y-axis

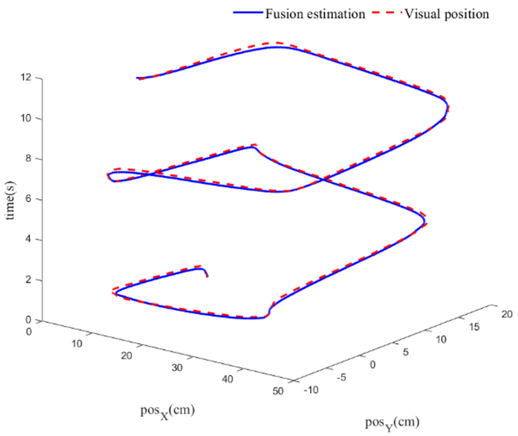

Fig. 9. Estimation of position of x-axis and y-axis over time

6 Conclusions

In this paper, a multi-source fusion location estimation method based on machine vision and strapdown inertial navigation is presented for indoor positioning of small UAVs with GPS invalid or unable to load. Based on AprilTags positioning and recognition technology, this paper defines NCS with AprilTags array, identifies tags with onboard camera, and obtains the spatial location of the UAV through the algorithm proposed in Sect. 3. Due to processor performance and power constraints, the location estimation obtained by the onboard image processing unit running the visual localization algorithm is more stable and not affected by the integral effect, but with high latency and unpredictable mutations, it is difficult to directly apply to the cascade controller. The position estimation of strap-down inertial navigation has fast response speed and strong anti-mutation ability, but it is susceptible to serous interference from measurement error and integral effect, and it is difficult to operate independently. Based on the idea of complementary filtering, combined with the multi-source information fusion algorithm, the third-order fusion complementary filtering algorithm is used to achieve the complementary filtering of the two estimation results, and the corresponding fast and reliable speed and location estimation is obtained. Finally, based on the self-developed four-rotor UAV experimental platform, the validity and reliability of the algorithm are verified by sampling.

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