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Concept of INS/GPS Integration Algorithm Designed for MEMS Based Navigation Platform

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Abstract. Nowadays, along with the advancement of technology one can notice the rapid development of various types of navigation systems. So far, the most popular satellite navigation, is now supported by positioning results calculated with the use of other measurement system. The method and manner of integration will depend directly on the destination of developed system. To increase the frequency of readings and improve the operation of outdoor navigation systems, one can support satellite navigation systems (GPS, GLONASS ect.) with inertial navigation (INS/GPS systems). For the last two decades, due to the miniaturization in electronics it is possible to build GPS/INS systems with the use of low cost MEMS devices. The following study presents the concept of Kalman filter based integration algorithm designed for cheap micro – electronic navigation platform. The tests of considered algorithm were made with the use of MEMS smartphone sensors. Subsequently the results of the study were analyzed to determine the accuracy of featured algorithm.

Keywords: integrated navigation, INS/GPS, MEMS IMU, inertial sensors.

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Introduction

It can be noticed, that for the last decade, social change is connected with the development of technology and electronics. Almost all aspects of human life have been changed by the application of new technical solutions. Similar consideratierations are made in order to increase the functionality of satellite navigation systems. Positioning results from GPS and GLONSS systems were sufficient in the 90s. Currently, despite the significant development, satellite navigation still has a number of limitations such as:

- inability to perform in – door measurements,
- inability to perform measurements in tunnels, under bridges, in storey garages,
- limited ability to perform measurements in urban canyons and wooded areas,
- not sufficient for augmented reality applications.

Due to these limitations, satellite systems must be supported in order to meet the users requirements. Over the years, scientists have developed a number of strategies to increase functionality of GNSS navigation. One group of methods is based on the use RF signals from other sources (Wi-Fi, Zigbee) (Rapinski, Cellmer 2016; Rapinski, Smieja 2015; Janicka, Rapinski 2016). The second group presupposes the use of IMU (Inertial Measurement Unit) combined in inertial navigation system (INS). Use of INS allows to increase frequency, availability and accuracy of positioning results. Such combined systems are called INS/GPS integrated navigation (Groves 2013; Noureldin *et al.* 2012; Grewal *et al.* 2013). Expensive INS are used for many years in marine, aviation and missile navigation. Nowadays, through the use of MEMS technology (Micro Electro-Mechanical Systems), they have become available for a large number of users (Solimeno 2007; Syed *et al.* 2007; Tomaszewski *et al.* 2015; Zhao 2011; Georgy *et al.* 2011; Noureldin *et al.* 2009).

Most frequently INS consists of six components: three accelerometers and three gyroscopes. Perpendicular orientation of these sensors implements the body coordinate frame of the unit (Fig. 1). To improve the accuracy of inertial navigation sometimes other sensors are added (odometer, magnetometer and barometer). Construction of the measurement unit provides readings of the angular velocities and linear accelerations in three mutual orthogonal directions. These measurements allows to determine the position, velocity and attitude without the involvement of external signals. At the same time, due to the relatively high noise and the accumulation of errors, the MEMS – based inertial navigation cannot be used as a standalone navigation system. Combination of GPS and INS results reduces the incremental inertial navigation errors. Simultaneously such integration makes it possible to use cheap navigation in places where it was previously unworkable (Woodman 2007; Noureldin *et al.* 2012; Groves 2013; Grewal *et al.* 2013).

The following study presents the concept of INS/GPS algorithm, designed for the low cost platforms. Subsequently the results of designed calculation method functionality test are presented. The studies were conducted with the use of readings from low-cost MEMS sensors installed within Samsung Galaxy S5 smartphones (Fig. 2). Proposed algorithm can be used in all MEMS – based INS/GPS platforms, as it was described in (Tomaszewski *et al.* 2015) The results of conducted research were analyzed in order to determine the functionality of developed algorithm.

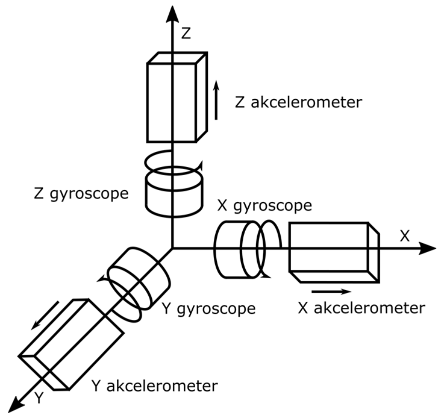

Fig. 1. Inertial Navigation System body frame (Source: own elaboration)

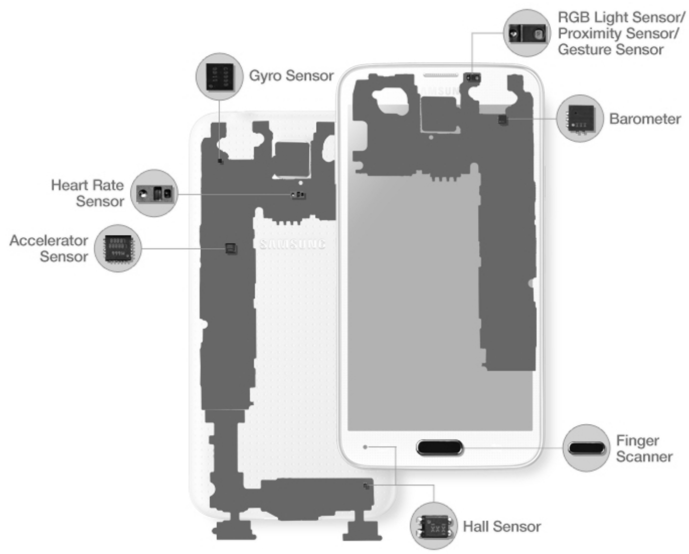

Fig 2. MEMS inertial sensors installed within Samsung Galaxy S5 smartphone
(*Source*: https://news.samsung.com/global/10-sensors-of-galaxy-s5-heart-rate-finger-scanner-and-more)

Basic concept of Kalman Filtering

For the purpose of INS/GPS integration the Kalman filter (KF) is used. The main idea of Kalman filtering is to utilize all of the available measurements, regardless of their precision, to estimate the current state of the system by appropriately weighting these measurements. By completion of this task, KF provides optimal least mean variance estimation of searched states (Kalman 1960; Welch, Bishop 2006). In case of INS/GPS integration there are usually errors of values calculated by the INS system (Solimeno 2007; Noureldin *et al.* 2009, 2012; Zhao 2011; Groves 2013; Grewal *et al.* 2013). Kalman filtering also provides information considering accuracy of performed calculations to determine the impact of each observable on the final result. KF consists of two phases: prediction (time update) and correction (measurement update) (Noureldin *et al.* 2012). The idea of prediction is to propagate system state and its covariance from epoch $\boldsymbol{k}-1$ to $\boldsymbol{k}$, on the basis of designed model. This phase consists of two steps: (1) calculating the predicted state vector $\hat{\boldsymbol{x}}_{\boldsymbol{k}}(-)$ and (2) calculating covariance of predicted state $\boldsymbol{P}_{\boldsymbol{k}}(-)$. In correction phase predicted state is compared to measurement to update previous estimate and produce optimal KF output. This phase consists of three steps: (3) calculating Kalman Gain $\boldsymbol{K}_{\boldsymbol{k}}$, (4) updating predicted state $\boldsymbol{x}_{\boldsymbol{k}}$ with measurement vector $\boldsymbol{z}_{\boldsymbol{k}}$ and (5) and updating error covariance $\boldsymbol{P}_{\boldsymbol{k}}$. Summarizing, KF comprises five equations which operate in a sequential manner (Noureldin *et al.* 2012; Grewal *et al.* 2013; Groves 2013). The idea is depicted in Figure 3.

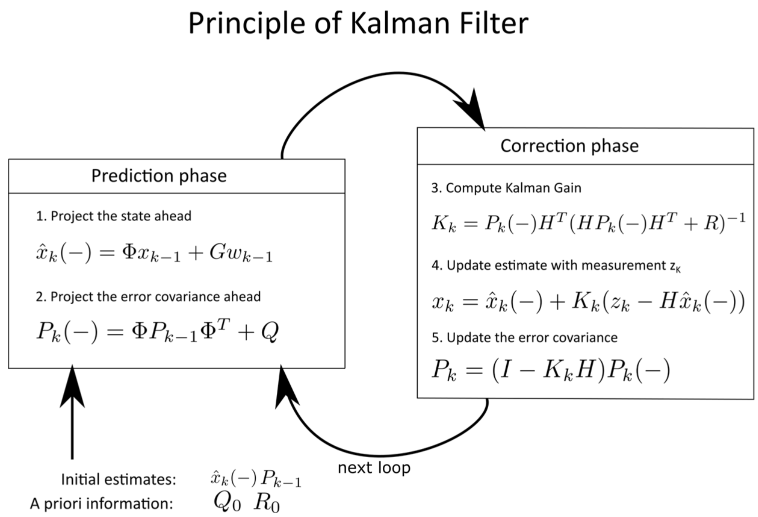

Fig. 3. The idea of Kalman Filtering (*Source*: own elaboration)

As it can be noticed in Figure 3, filter starts with some initial information: $\hat{\boldsymbol{x}}_{\boldsymbol{k}}(-)$ – initial state vector and $\boldsymbol{P}_{\boldsymbol{k}-1}(-)$ – initial state covariance matrix. These values are usually considered to be 0 or adopted from the previous filter operation. Second information is delivered at the beginning of KF is a priori value of $\boldsymbol{Q}_0$ – process noise covariance matrix and $\boldsymbol{R}_0$ – measurement noise covariance matrix. They are estimated on the basis of prior experience with the system and are tuned to get the best estimates of the states.

In the predication phase matrix $\boldsymbol{\Phi}$ – state transition matrix, is responsible for the state propagation from epoch $\boldsymbol{k}-1$ to $\boldsymbol{k}$. Values $\boldsymbol{G}$ – noise distribution matrix/control-input model and $\boldsymbol{w}_{\boldsymbol{k}-1}$ – process noise vector/control vector takes into account the coupling of common noise disturbances into various components of state dynamics.

In the correction phase matrix $\boldsymbol{K}_{\boldsymbol{k}}$ – Kalman gain is a weighting factor computed in such a way that it minimizes the mean squared error of the estimate. Matrix $\boldsymbol{H}$ – design matrix, defines the linear relationship between the predicted state and measurements that can be made. The measurement vector $\boldsymbol{z}_{\boldsymbol{k}}$ consists of all the observations that will be used to correct the predicted state od the system $\hat{\boldsymbol{x}}_{\boldsymbol{k}}(-)$.

INS/GPS integration method

Tested algorithm was designed based on the idea of loosely coupled INS/GPS integration. Selection of this approach stems from the fact that smartphone only provide calculated GPS coordinates and do not allow to access raw observations. The band sensors installed inside the Samsung Galaxy S5 smartphone allowed to add magnetometer readings to the traditional INS structure. Thanks to this solution filter results gain independent north determination in each epoch. The use of low quality sensors require the number of changes to be applied compared to the traditionally used integration architectures: in state vector instead of INS system position errors, velocity errors and attitude errors, values of position velocity and Euler angles were placed, calculated coordinates are in UTM system instead of WGS84 to simplify navigation equations, the inertial system errors are calculated at the end of the filter and added before each epoch as a feed back loop, INS measurement values are added inside the prediction model of the filter.

The implementation of these assumptions induced that designed filter does not meet all the conditions of Kalman filtering. Therefore, it is defined as a KF based type of calculations. According to these assumptions the state vector is as follows:

$$\hat{x}_k^- = \left[P_{3\times1}, V_{3\times1}, E_{3\times1}\right]^T, \quad (1)$$

where:

$\boldsymbol{P}_{3\times1}$ – is a vector of X,Y UTM coordinates and elipsoidal height h,

$\boldsymbol{V}_{3\times1}$ – is a vector of velocities in UTM coordinate system,

$\boldsymbol{E}_{3\times1}$ – is a vector of Euler angels.

On the basis of state vector it can be seen that, apart from increasing the frequency and availability of navigation, the use of inertial sensors allows for attitude calculation. Due to this fact the smartphone becomes PVA (Position, Velocity Attitude) navigation system. This increases the possibilities of the device responding to new requirements for navigation systems.

Measurement values are added to the filter with the use of $\boldsymbol{u}_{k-1}$ vector, in this case called control vector.

$$\boldsymbol{u} = \begin{bmatrix} f_x^E \\ f_y^E \\ f_h^E \\ g_x \\ g_y \\ g_z \\ -g_z^g v_y + g_y^g v_h \\ g_z^g v_x + g_x^g v_h \\ -g_y^g v_x + g_x^g v_y \end{bmatrix}, \tag{2}$$

where:

f_x^E, f_y^E, f_h^E – are values of linear acceleration readings transformed to UTM system,

g_x, g_y, g_z – are gyroscope readings with corrected drift,

v_x, v_y, v_h – are velocities in local coordinate system,

g_x^g, g_y^g, g_h^g – values repsesenting impact of ECEF – ECI movement and UTM – ECEF movement on calculated velocities.

State transition matrix A and control – input model were created to add property all values. Initial state covariance matrix $\hat{P}_{k-1}^-$ and process noise covariance were calculated on the basis of known accuracy of inertial sensors. For presented prediction model a suitable measurement vector was designed:

$$z_t = \left[P^{GPS}, V^{DOPP}, y^{mag} \right]^T, \tag{3}$$

where:

P^{GPS} – is a vector of GPS coordinates transformed to UTM coordinate system,

V^{GPS} – is a vector of Doppler velocities transformed to UTM coordinate system,

y^{mag} – is the value of magnetic North (yaw angle), calculated on the basis of magnetometer readings.

Values of measurement covariance matrix are taken from the GPS system and on the basis of known magnetometer accuracy. The design matrix H has a simple form, due to the fact that predicted values are the same as measured. At the end of the filter the difference between state prediction and filter final state is defined as noise and recalculated as INS system errors. Simplified schema of INS/GPS algorithm is presented on Figure 4.

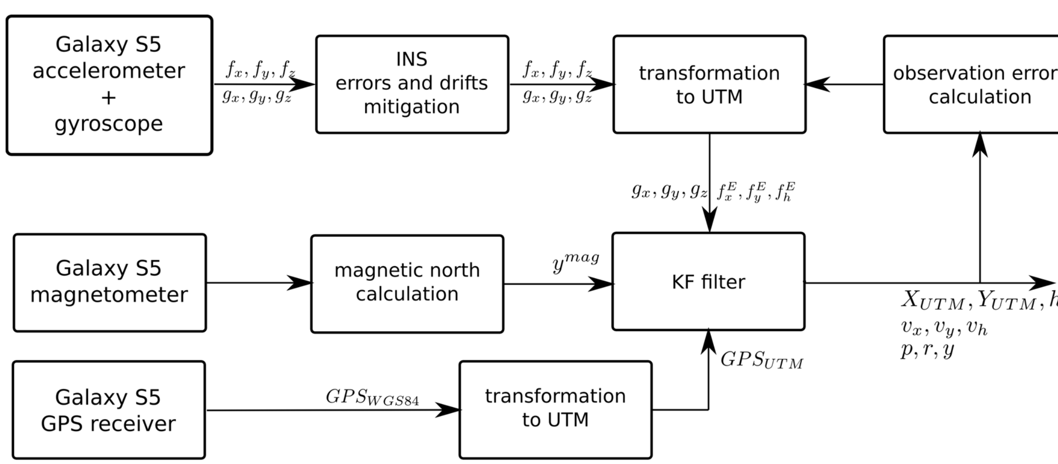

Fig. 4. Schema of designed INS/GPS integration algorithm (*Source*: own elaboration)

At current stage, inertial sensors readings and results of satellite positioning are streamed with the use of UDP protocol from smartphone to the computer via wifi network. All calculations are made in real time within the computer. Communication is based on sending two sentences. The first sentence appears with each GPS epoch and contains the results of satellite positioning and inertial sensors measurements. Simplified form of the sentence is presented in the Figure 5 below.

GPS SOW	GPS Id	GPS WGS84 coordinates	GPS WGS84 coordinates errors	acc Id	x, y, z accelerometer readings	gyr Id	x, y, z gyroscope readings	mag Id	x, y, z magnetometer readings
[s]	1	[degrees]	[m]	3	[m/s^2]	4	[rad/s]	5	μT

Fig. 5. First sentence of communication protocol (*Source*: own elaboration)

The second sentence appears with 50 Hz frequency. It consists of accelerometer, gyroscope and magnetometer readings. Simplified form of the sentence is presented in the Figure 6 below.

GPS SOW	acc Id	x, y, z accelerometer readings	gyr Id	x, y, z gyroscope readings	mag Id	x, y, z magnetometer readings
[s]	3	[m/s^2]	4	[rad/s]	5	μT

Fig. 6. Second sentence of communication protocol (*Source*: own elaboration)

Element deployed to synchronize measurement data is GPS SOW (GPS Second Of Weak). A simple form of the algorithm makes it possible to be applied in all android devices equipped with suitable sensors. Regardless of the phone model the program installed inside the device will transmit measurement data according to the method described above. Form of the algorithm and the communication protocol makes the developed method universal.

Field tests of algorithm

For the purpose of functionality check of designed algorithm, a field test was conducted. Samsung Galaxy S5 was fixed in a moving vehicle. Car travelled the route planned inside Kortowo campus. Vehicle was moving around the urban area with trees along side of the road. During the test, the phone performed 1Hz GPS observations and 50 Hz INS measurements. Subsequently collected data have been calculated with the use of INS/GPS algorithm presented above. At the beginning of the trial, a short 3 minute alignment period was performed. One minute of gyro and accelerometer measurements were averaged. These values were used as initial bias estimates. Next the values of pith and roll angles were calculated. Afterwards the magnetic induction readings were used to calculate magnetic north (yaw angle). Values of initial bises, pith, roll and yaw were input to the AHRS filter used to calculate external orientation of the smartphone.

As a reference to the smartphones calculations, a high-quality Thrimble geodetic receiver was udes. Thrimble receiver was connected to the GNSS antenna mounted at the roof of the vehicle. The reference trajectory was obtained using double frequency GNSS phase and code measurements kinematic post-processing (OPNT reference station). The mean error of position obtained from GNSS processing calculated by the Topcon Tools software was 0.03 m.

Then the results of Galaxy S5 GPS and INS/GPS were compared to the reference trajectory, to verify how the use of the INS sensors will change the positioning accuracy. Since the results obtained from the integrated navigation has 50 Hz frequency and satellite positioning is performed with 1Hz frequency, to perform results comparison, a special approach was applied. Instead of comparing the coordinates of joint epochs, a perpendicular distance from the reference trajectory has been calculated for all results. Thus, all calculations from integrated system were taken into account and the resulting values from the two systems were compared statistically. Obtained trajectories are presented in Figures 7 and 8.

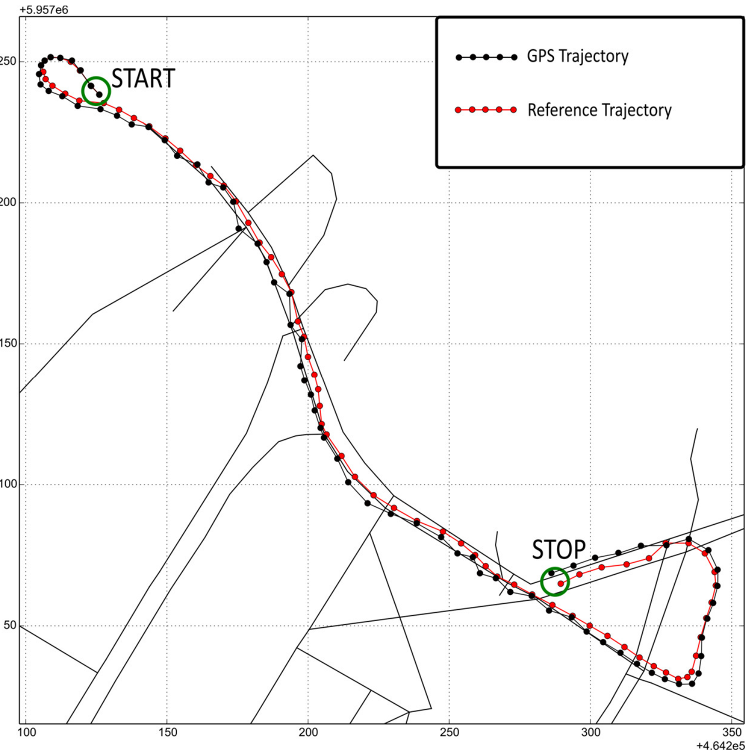

Fig. 7. Tested GPS trajectory (*Source*: own elaboration)

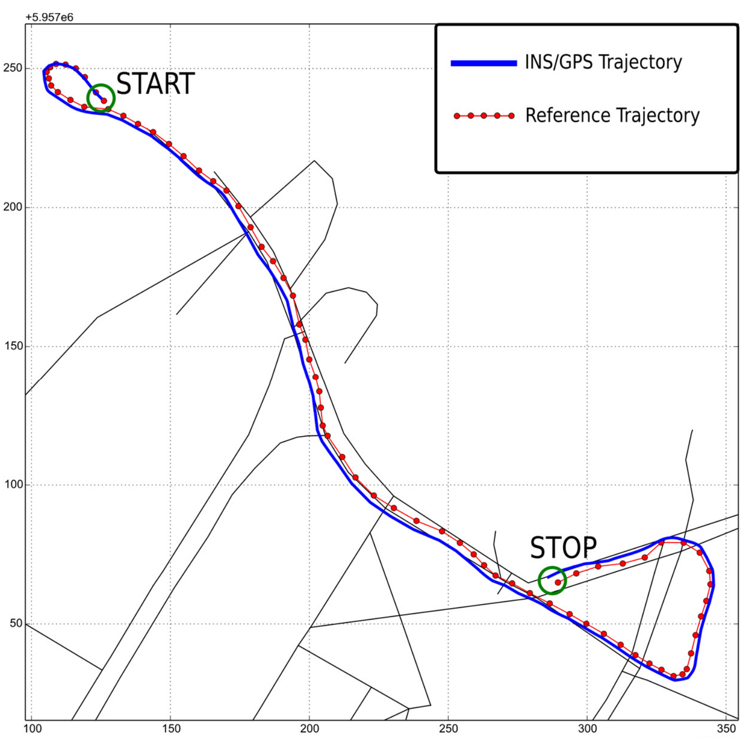

Fig. 8. Tested INS/GPS trajectory (*Source*: own elaboration)

In the figures above, coordinates of reference trajectory is depicted in red. Results from INS/GPS integrated algorithm are depicted as a blue line and GPS trajectory is marked in black. As it can be noticed, the use of integrated algorithm significantly increased the number of obtained coordinates. An INS/GPS algorithm smoothed values from absolute positioning presumably reducing the impact of satellite positioning errors. Statistical analysis of the differences between INS/GPS, GPS results and reference trajectory is comprised in Table 1.

Table 1. Statistical analysis of the distances from reference trajectory (*Source*: own Elaboration)

Differences analysis [m]						
	Min	Max	Mean	Median	Standard Deviation	Variance
GPS	0.04	8.10	3.78	3.01	2.31	5.34
INS/GPS	0.00	6.34	2.54	2.02	1.99	3.96

Based on the data from Table 1 it can be concluded that the use of inertial sensors raised accuracy of absolute positioning. Mean distance from reference trajcectory is over 1 m higher than in the case of GPS positioning. Additionally, integrated results are characterized by lower variability, as seen in the values of standard deviation and variance. Thus, one can say that the full support of smartphones inertial sensors improves vehicle navigation.

Conclusions

The results presented above clearly indicate the improvement of vechicle satellite navigation accuracy and funcionality while using support of inertial sensors. Despite the low-quality IMU that is mounted inside smartphones, INS/GPS trajectory is smooth and better suited to reference trajectory than absolute GPS positioning. Considerations presented in the article constitute the first step in creating platform independent integrated navigation. Initial assumptions presented above require further testing in different conditions and terrain along with limited visability of GPS satellites. However, it should be noted that first results are promising and tend to carry out further research. The use of sensors installed inside smartphones introduces certain limitations that must be delt with. The lack of certainty as to the accuracy and the model of used measuring modules, inability to define the full error characteristic of INS are first three that start the list of the aforementioned problems. In addition, inside the smartphone, one does not have access to the raw GPS observation. All these factors limit the possibilities of designing algorithm, however allow to search for some new solutions. Therefore, further research will be conducted in order to develop an algorithm where the biggest focus is placed on its versatility.

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