MULTI-SENSOR FUSION FOR COST-EFFECTIVE PRECISE VEHICLE POSITIONING

Hojun Kim[1] and Impyeong Lee[2]
[1]Dept. of Geoinformatics, The Univ. of Seoul, 163 Seoulsiripdaero, Dongdaemungu, Seoul, Korea,
Email: zzimss@uos.ac.kr
[2]Dept. of Geoinformatics, The Univ. of Seoul, 163 Seoulsiripdaero, Dongdaemungu, Seoul, Korea,
Email: iplee@uos.ac.kr

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ABSTRACT: As the advantage of safety and convenience, an autonomous car and ADAS are being actively researched. One of the main challenge of the systems is to precisely determine the position of the vehicle. To solve this problem, sensor fusion methods are mostly used in many recent studies. In this work, we design a workflow for a vehicle position estimation system based on a sensor fusion approach and evaluate the accuracy of the proposed algorithm. The algorithm uses in-vehicle sensors, GPS, image sensors and road characteristics information for position estimation. The proposed sensor fusion method determines the vehicle positions by the following procedures. First, a relative trajectory is calculated using in-vehicle sensors only. This process is called a dead reckoning step. Then, we perform a bundle adjustment algorithm to estimate the position and direction of the vehicle using images and the initial values derived from the previous step. Through this step, we can determine the vehicle position more precisely. The sensor fusion procedure is performed using an EKF. The EKF calculates vehicle positions whenever the sensory data are acquired from in-vehicle sensors, a GPS and a camera. If road characteristics information is acquired from other sensors, it also can be combined for accurate position estimation. For the experiment, we designed a sensory data acquisition system and installed it on a vehicle. We also installed a precise position measuring equipment to evaluate the proposed algorithm. The estimation is performed using in-vehicle sensor only method and the proposed sensor fusion method. The RMS errors of the estimated positions from the proposed method are about 1.6 m. This experimental results show nearly 90% improvement in accuracy compared with the results from the in-vehicle sensor only method. The algorithm may be used for applications requiring accurate driving route estimation such as autonomous car and ADAS.

1. INDTORUCTION

For the reliable operation of autonomous vehicles, providing accurate current position is one of the important components. It is also an essential part for advanced driver assistance systems (ADAS), collision warning systems and autonomous lane change systems. Most of these systems are based on a Global Positioning System (GPS) to obtain the positioning data. However, the stability and accuracy of the GPS is not sufficient for the above applications. Therefore, it is necessary to use some other methods to compensate the weakness of GPS signals. There are many studies to overcome the limitation of GPS signals. The most common approach is using additional sensory information.

Google employs many sensors such as cameras, radars, 3D LiDAR, GPS/INS/Encoder, even computer and others for self-driving cars. Other automobile manufacturers also focus on autonomous vehicles with high price and high performance sensors (Franke, 2013). Those companies already develop and operate their autonomous vehicles in a test area. However, in order to commercialize them, it can be a significant obstacle that the prices of sensors are too expensive. Therefore, there are several attempts to replace high-priced sensors using inexpensive sensors with a sensor fusion algorithm. To reduce error and overcome high price, some researchers combine GPS and in-vehicle sensors. Jo et al. proposed a vehicle localization algorithm using distributed vehicle state estimation. This study employed Interacting Multiple Model (IMM) filter for better accuracy (Jo, 2010). And another paper combine GPS and in-vehicle sensors using a Kalman filter (Jong, 2010).

Another frequently used additional sensor is a camera. It retains a low price compared to other sensors but the results are promising. There are many studies related to visual odometry. The results seem to be helpful for estimating vehicle positioning. A research use a camera with landmark information (Mattern, 2010). It also use ground points, a digital map and in-vehicle sensors to localize the vehicle. Kim et al. (2011) use omnidirectional cameras, in-vehicle sensors and an odometer. These studies provided accurate results but the used sensors are still too expensive to commercialize and some studies only focused on limited conditions or specific applications. Map-based localization is also studied. Most approaches follow a principle of loop-closing in the Simultaneous Localization and Mapping (SLAM) area. A loop-closing technique is to mitigate localization errors by revisiting the place visited in the past and adjusting the accumulated errors in the meantime. In the same context, it is possible to precisely estimate positions and attitudes of a car by observing the previously mapped area. This can give constraints for localization, and relieve the accumulated errors. Another advantage of map-based approaches is that such a system is much less affected by the signal reception environment unlike GPS.

In many map-based localization studies, various kinds of data are employed as map data. Digital Elevation Model (DEM) and 3D building layer from the Geographic Information System (GIS) were used to estimate positions and attitudes of a vehicle and constrain the reconstruction process (Larnaout, 2012). Furthermore, any kind of geo-referenced information can play the role of a map. Laftchiev et al. constructed a map using highly accurate IMU data to compensate pitch errors of data and IMU mounted on a vehicle (Laftchiev, 2015). A 3D LiDAR point cloud database is employed in vehicle localization (Yoneda, 2014). In this study, a scan feature quantity measure was proposed to effectively employ the point cloud map. Meanwhile, geo-referenced image databases also can be used. Some of them provide semantic images such as landmarks and traffic signs. Qu et al. used traffic sign images as ground control information for a bundle adjustment process (Qu, 2015). Others provide a geo-referenced image stream like Google Street View. There has been some research which performed vehicle localization using topologic and metric image sequences and road network to overcome the ambiguity of dead reckoning (Badino, 2011).

In this paper, a car position estimation algorithm using GPS, in-vehicle sensors and georeferenced images is proposed for precise car navigation. The algorithm is composed of three main processes: dead reckoning, image georeferencing and localization. To estimate an accurate result, the in-vehicle sensors, GPS and image information are used. For combining this sensor information, the Extended Kalman Filter (EKF) is employed. As a result of the proposed algorithm, accurate vehicle position and driving direction is provided. The following section describes our vehicle position estimation system. Then, experimental results are described in section 3. Finally, section 4 concludes this paper.

2. FRAMEWORK

Owing to its low price and good accuracy, the GPS is an essential part of car navigation systems. But the GPS is not suitable for autonomous vehicles because of weakness such as multipath or signal outage. Therefore, this paper proposes a vehicle position estimation system based on a vision-based localization approach. This system can estimate the vehicle position and driving direction more precisely using a sensor fusion method. The structure of this system can also easily add more sensor information related to car position such as traffic lane information.

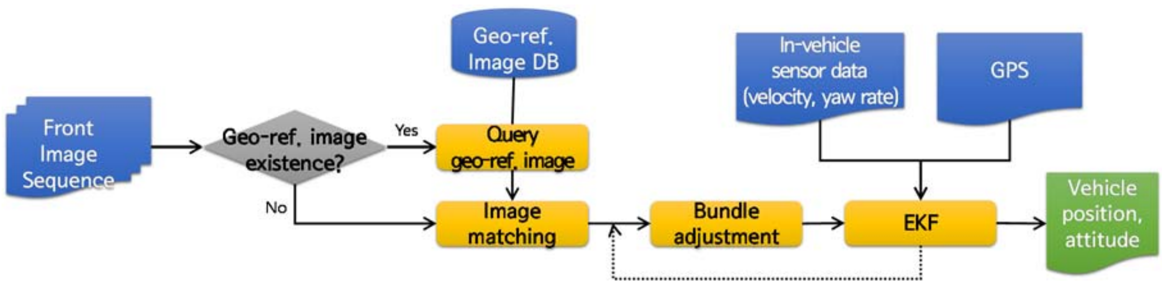

Figure 1. Framework of the proposed car navigation system

Figure 1 shows the overall process of a vision-based car position estimation system. The in-vehicle sensors provide yaw rate and velocity through the controller area network (CAN) bus. The GPS provides global position of the car. And position and direction of the vehicle can be derived from georeferenced images and frontal images through image matching and a bundle adjustment process. The EKF process combines individual sensory data and estimates final position and direction of the vehicle. Each of these steps is described in detail below.

2.1 Dead Reckoning

The basic component of the framework is the dead reckoning process, in which in-vehicle sensors are used to calculate the vehicle’s position. The dead reckoning process is to determine the current vehicle position from the previous position using moving direction and travel distance.

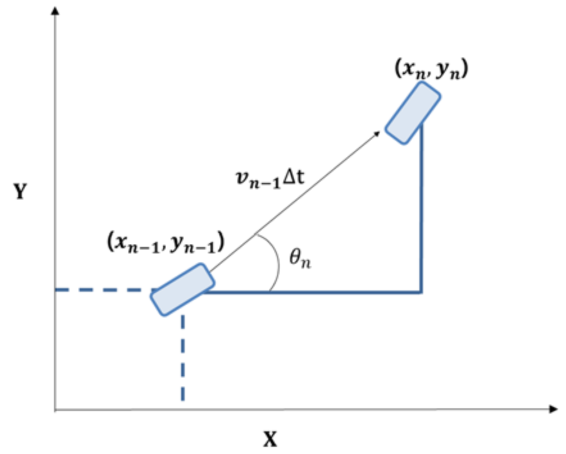

Figure 2. Position and direction estimation model

A vehicle position and driving direction can be derived using velocity and yaw rate from in-vehicle sensors, as shown in Figure 2. If we have knowledge of the position and measurement of the velocity and direction at the previous time (n-1), we can determine vehicle position and driving direction at the current time (n). Through this, the position and direction of the vehicle can be calculated as follows:

$$\begin{bmatrix} x_n \\ y_n \end{bmatrix} = \begin{bmatrix} x_{n-1} \\ y_{n-1} \end{bmatrix} + v_{n-1} \begin{bmatrix} cos\,\theta_{n-1} \\ sin\,\theta_{n-1} \end{bmatrix} \Delta t \quad (1)$$

$$\theta_n = \theta_{n-1} + w_{n-1}\Delta t. \quad (2)$$

With these incremental equations, if the time interval is reasonably small, we can determine the position and attitude at each time epoch relative to the initial status. If we know at least the initial status in an absolute coordinate system, we can determine the status at all the time epochs in the same absolute system.

2.2 Georeferenced Image Database

Geo-referenced images can be defined as associated images with geographic information. The geographic information mainly associated with the geo-referenced image in this study is the position and attitude of a camera when a geo-referenced image is captured in the world coordinate system. Moreover, positions of the projected geographic features onto the geo-referenced image are also associated. They can play the role of a map which provides geographic information for the car navigation system.

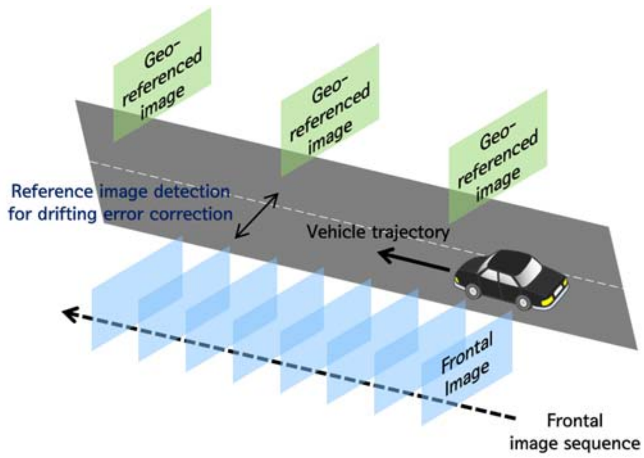

Figure 3. Concept of the car navigation using georeferenced image database

The basic concept of the geo-referenced image database in this study is to correct the accumulated localization errors by detecting the precisely geo-referenced images and comparing the vehicle data to them. The geo-referenced images are sparsely distributed through the vehicle trajectory as in Figure 3. If the geo-referenced images are detected, the vehicle localization system compares frontal image sequences from a vehicle with corresponding geo-referenced images. Localization errors can then be derived from the results of such a comparison. The position and attitude of the car can then be precisely refined by using the estimated errors.

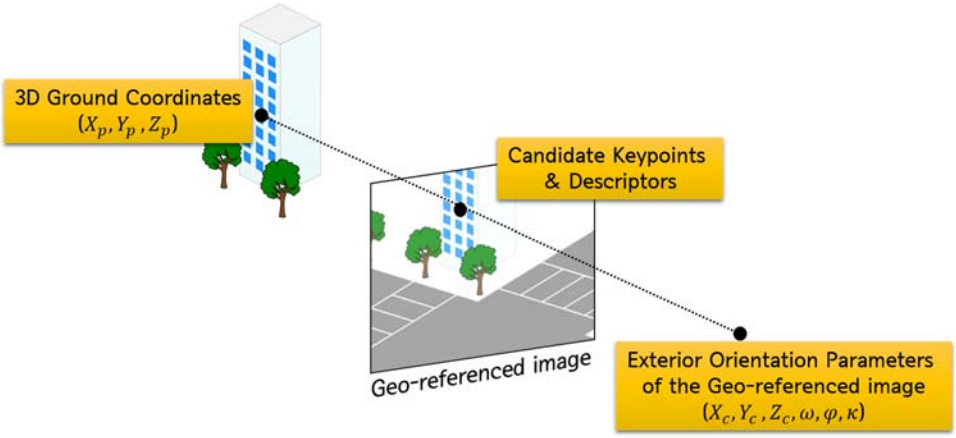

Figure 4. Three data elements of the georeferenced image database

In this research, the geo-referenced image mainly contains three data elements as in Figure 4. Each geo-referenced image has its camera position and attitude at its capture time. The second element is the 3D ground coordinates of the projected subjects onto each geo-referenced image. The two aforementioned elements are precisely determined in advance of vehicle driving. The last is a set of candidate image points (keypoints) and their descriptors which describe pixel intensity near each image point. They are extracted from the geo-referenced image, and they are essential to compare images. The left part of Figure 1 shows how the geo-referenced image database is employed in the vehicle localization system. Whenever a frame of frontal image sequences is captured, the system queries the corresponding geo-referenced image. If the system returns a positive answer to the query, the searched geo-referenced image is used as an input datum with frontal image sequences for image matching process. The image matching process is to extract image feature correspondences between input data. Previously extracted keypoints and their descriptors from the geo-referenced images participate in the image matching process. Bundle adjustment is then performed with the results of image matching. In this step, the camera position and attitude, and 3D ground coordinates involved with the geo-referenced image can give constraints for localization. This helps precisely estimate the positions and attitudes of a car and correct the accumulated localization errors.

2.3 Localization Using a Kalman Filter

At the localization step, an EKF is used to estimate the vehicle position and orientation. GPS data, in-vehicle sensors and georeferencing results are combined to get improved estimation results. A process for the EKF prediction step (time update) is given by

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$$

$$P_k^- = AP_{k-1}A^T + Q. \tag{3}$$

and the update step (measurement update) is given by

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$$

$$P_k = (I - K_k H)P_k^-$$

$$\mathrm{z} = \mathrm{Hx} + \mathrm{v}, \qquad \mathrm{v} \sim (0, \mathrm{R}). \tag{4}$$

The vehicle position (x, y, z) and driving direction (θ) are estimated by integrating sensory data. According to (1) and (2), which are derived from the dead reckoning step, the state is calculated as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{\theta} \\ \dot{v} \\ \dot{w} \end{bmatrix} = \begin{bmatrix} v \cdot cos\theta \cdot \Delta t \\ v \cdot sin\theta \cdot \Delta t \\ 0 \\ w \cdot \Delta t \\ 0 \\ 0 \end{bmatrix}. \tag{5}$$

At the measurement step, the filter computes the Kalman gain value and state and covariance values. In accordance with the measured sensor type, three individual measurement models are designed. The measurement model for in-vehicle sensors is as follows:

$$\mathrm{Z_{CAN}} = [\mathrm{v\ w}]^{\mathrm{T}}, \qquad \mathrm{H_{CAN}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathrm{R_{CAN}} = diag([\sigma_v^2\ \sigma_w^2]). \tag{6}$$

Another measurement model for GPS data is calculated as

$$Z_{GPS} = [\mathrm{x_{GPS}\ y_{GPS}\ z_{GPS}}\ ]^{\mathrm{T}}, \qquad \mathrm{H_{GPS}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathrm{R_{GPS}} = diag([\sigma_x^2\ \sigma_y^2\ \sigma_z^2\ ]). \tag{7}$$

and the measurement model for georeferencing results is calculated as follows:

$$Z_{AT} = [x_{AT}\ y_{AT}\ z_{AT}\ \theta_{AT}\ ]^T, \qquad \mathrm{H_{AT}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\mathrm{R_{AT}} = diag([\sigma_x^2\ \sigma_y^2\ \sigma_z^2\ \sigma_\theta^2]). \tag{8}$$

3. EXPERIMENTAL RESULT

3.1 Test System and Data

We construct a data acquisition system to verify the performance of the proposed algorithm. The system can acquire in-vehicle sensors, GPS data and image data. Reference data for accuracy evaluation are also acquired at the same time. The reference vehicle position was obtained from POS-LV 420, a commercial positioning solution for land-based vehicles. The accuracy of the reference equipment is summarized in Table 1 (Applanix, 2015). Figure 5 shows the data acquisition system that contains a front view camera, GPS, in-vehicle sensors and the reference data acquisition system. Inside of the car, we installed a laptop for collecting and monitoring the sensory data in real time.

Table 1. Accuracy of the referenced equipment

	Parameters	Post processing	RTK	DGPS
With GPS	X, Y [m]	0.020	0.035	0.300
	Z [m]	0.050	0.050	0.050
	Roll, Pitch[°]	0.015	0.015	0.015
	Heading[°]	0.020	0.020	0.020
GPS Outage (60 seconds)	X, Y [m]	0.120	0.0340	0.450
	Z [m]	0.100	0.270	0.560
	Roll, Pitch[°]	0.020	0.020	0.020
	Heading[°]	0.020	0.030	0.030

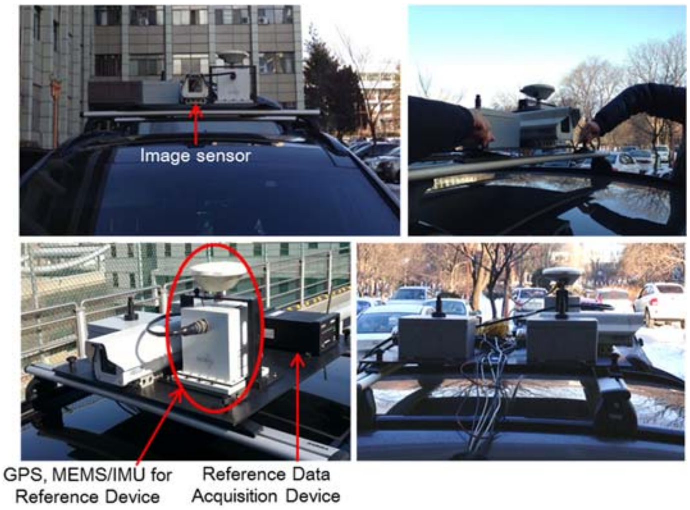

Figure 5. The data acquisition system

The data were acquired near the University of Seoul, Korea. Figure 6 shows the test site and trajectory. It took around 510 seconds and the distance was about 1.7 km and the start point and the end point were almost the same. During the driving, in-vehicle sensor data, images and reference data are acquired. For implementing the proposed algorithm, the reference image database and georeferencing result of driving images are required. In this test, 250 images were used.

Figure 6. The test site and trajectory (a red line)

3.2 Estimation Results

To verify the accuracy, we define the reference data as the true values and compared them with the results of the in-vehicle sensor only method and sensor fusion method. We assumed that GPS signal outage occurred in the entire area. The estimated trajectories are shown in Figure 7. It shows the reference trajectory (the black solid line), the in-vehicle sensor only trajectory (the red dashed line) and the proposed sensor fusion method trajectory (the blue dotted line). The proposed method is much closer than in-vehicle sensor only method. Figure 8 shows the distance difference comparing to the reference trajectory. The distance difference from the in-vehicle sensor only method (the red solid line) has continuously high error. In contrast, the distance difference from the sensor fusion method are going down when the georeferenced image data are obtained. Table 2 indicates the position estimation errors. The RMS (root-mean-square) errors of the proposed sensor fusion method is about 90% lower than the in-vehicle sensors only method.

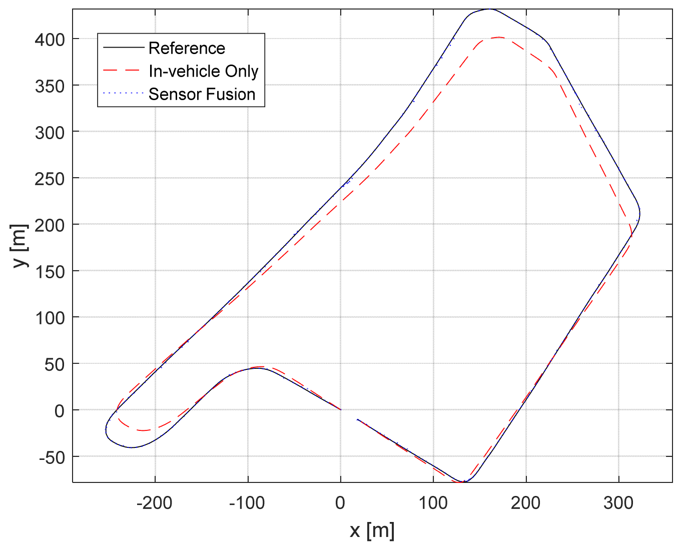

Figure 7. Estimated trajectory

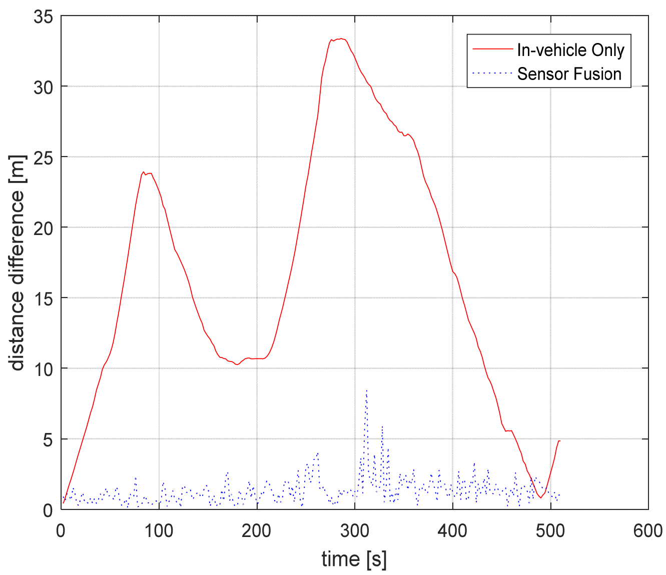

Figure 8. Comparison of position difference

Table 2. Errors of position estimation

Unit [meter]	In-vehicle Sensors			Sensor Combining		
	X	*Y*	*Distance*	*X*	*Y*	*Distance*
Mean	3.72	-6.73	16.28	-0.09	0.34	1.31
STD	7.78	15.22	9.25	1.02	1.24	0.98
RMS	8.61	16.62	18.71	1.02	1.28	1.64
Min	-9.59	-32.16	0.42	-4.60	-3.50	0.09
Max	14.50	21.18	33.38	2.91	7.10	8.46

4. CONCLUSIONS

In this paper, we proposed a sensor fusion system for vehicle position estimation. This system combines GPS, in-vehicle sensors and image data for accuracy improvement. An EKF model is adopted for sensor fusion. To verify the proposed method, we constructed a data acquisition and processing system. This system can collect in-vehicle sensors, GPS and image data. In addition, reference data are also obtained and treated as true values. The estimation accuracy of the proposed method is 90% lower than in-vehicle sensor only method even without GPS signals. In future work, we plan to test more data and improve the vehicle positioning accuracy.

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