Experimental comparison of RSSI-based localization algorithms for indoor wireless sensor networks *

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Abstract

In this paper, we investigate the actual performance of some of the best known localization algorithms when deployed in real–world indoor environments. Among the plethora of possible localization schemes, we focus on those based on radio signal strength measurements only, since they do not require extra circuitry that would result in higher cost and energy consumption. For a fair comparison, we have first gathered thousands of radio signal strength measurements in two different indoor environments. To estimate the channel model parameters and to compare the different localization algorithms these data have been used.

Categories and Subject Descriptors

C.3 [**Special-purpose and application-based systems**]: Real-time and embedded systems

General Terms

Algorithms Experimentation

Keywords

localization, RSSI, WSN, sensors, testbed, experimental

1 Introduction

Accurate and low-cost sensor localization is a critical requirement for the deployment of wireless sensor networks in a wide variety of applications. The topic is very well known and it has been widely investigated, mainly by means of simulations. Unfortunately, experimental studies have revealed that most of the state of the art localization algorithms, once deployed in real testbeds, achieve much worse performance than what predicted by the simulation analysis, in particular in indoor scenarios where the localization problem is exacerbated by a very hostile radio propagation environment. In fact, most of the localization algorithms proposed in literature makes use of the Received Signal Strength Indication (the RSSI) to get an estimate of the distance between transmitter and receiver (ranging). Unfortunately, the indoor radio channel is very unpredictable, since reflections of the signal against walls, floor and ceiling may result in severe multi–path interference at the receiving antenna. In static or slowly changing environments, this results in long–term random variations to the deterministic distance–vs–received power law dictated by the path–loss model. This random term will determine range estimation errors that, in turn, will lead to large localization errors.

A possible way to dramatically improve the ranging accuracy consists in using other physical-layer measurements than RSSI, such as the time–of–flight of pressure waves, or ancillary radio hardware, such as multiple and/or directional antennae. These solutions however generally are more energy demanding and/or require dedicated hardware, which results in more expensive devices. On the contrary, pure RSSI methods can be readily deployed in every wireless sensor network platform, since the RSSI circuitry is natively supported by most of the existing transceiver chipsets, with no extra hardware costs. Therefore, there is still a lot of interest in improving the performance of RSSI–based localization algorithms.

In this work we tackle the problem by presenting an accurate performance comparison among some well known RSSI–based localization algorithms in indoor environments. The aim of the study is to gain a better understanding of the actual potentialities and limits of common localization algorithms in indoor environments and to shed light on some still open questions, such as:

1. how many anchor nodes are needed to reduce the localization error below a certain limit?
2. is it true that complex estimation algorithms, such as Maximum Likelihood (ML), perform much better than simple ones, as Min–Max?

To this end, we have realized two testbeds in two different environments, which are representative of somehow typical indoor scenarios, namely an empty corridor and our research lab, i.e., a large room, cluttered with desks, chairs, computers, hubs, cables and persons engaged in their daily work life. We have then collected hundreds of RSSI measurements for each sensor and gathered all the data in two data sets, one for each environment. The data sets have been used to characterize the radio channel, estimating the parameters of the radio propagation models and of the random term. The localization algorithms have been compared over a number of different scenario which have been extracted from the set of collected measures.

Although we cannot claim that this work provides the ultimate answer to any of the above mentioned questions, in our opinion it offers some insight to move a step forward.

The remainder of this paper is organized as follows. Section 2 gives a short survey of the related work, with particular attention to the localization algorithms considered in our study. Section 3 presents the experimental setup used for the measurements. In Section 4, the parameters of the indoor radio channel model are estimated from the collected data. Section 5 reports the comparison

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among the experimental results obtained using the different localization algorithms. Finally, in Section 6 we summarize the results and conclude the paper.

2 Related Work

As previously mentioned, the literature on the topic is huge and an accurate survey of it is clearly out of the scope of this work. Rather, we focus on RSSI based schemes only, dwelling upon the algorithms that have been used in our study. A more comprehensive overview of the topic can be found, for instance, in [1, 2].

In general, localization algorithms assume the presence in the network of a limited number of reference nodes, referred to as *beacon* or *anchor* nodes, which know their own spatial coordinates and are used as reference points for localizing the other nodes, hereafter referred to as *strayed* nodes. Broadly speaking, the localization algorithms can be divided in two wide categories: range–based and range–free.

Range–based algorithms make use of the RSSI to estimate the distance between nodes. Then, different techniques, such as lateration [3], triangulation [4] or statistical inference [5], are used to estimate the position of strayed nodes with respect to the beacons. Unfortunately, RSSI–based ranging is severely affected by errors due to the unpredictable radio propagation behavior, especially in indoor environments. A poor ranging usually determines very loose position estimates and, hence, unsatisfactory localization performance. This limit has been remarked in [6, 7], where the authors state that the performance cannot improve significantly even using complex algorithms, being intrinsically limited by the ranging errors. However, such papers do not investigate how the ranging errors are affected by the number of anchor nodes and the accuracy of the radio propagation model. The ranging errors due to noisy RSSI values, however, can be mitigated through a series of refinement phases, as in Savarese [8] and Savvides [4].

In RSSI–based range–free algorithms, localization is still performed by exploiting the RSSI values that, however, are not used to estimate the distances between strayed and beacon nodes. Good results have been obtained by RSSI–mapping techniques, such as RADAR [9], which require to preliminary perform an accurate measurement campaign aimed at constructing a map of the radio signal strength received in the area of interest. Comparing the RSSI values received from the different beacons with the pre-built RSSI map, a node can estimate its own position in the area. Another family of range–free algorithms makes use of the RSSI samples to establish order relationships between nodes. A great advantage of this approach is its independence of the underlying channel. On the other hand, it makes it difficult to reach a low localization error even in the presence of a good radio channel.

In this paper we consider four algorithms, namely *Min–Max* [10, 11], *Multilateration* [10, 11] and *Maximum Likelihood* [5, 12] estimate for the range–based category, and the ROCRSSI [13] as a representative for the range–free algorithms.

Min–Max

Min–Max [10, 11] is a very popular localization algorithm, whose success is mainly due to its extreme implementation simplicity. Strayed nodes create an association between each beacon position and the strength of the radio signal received from that beacon. Inverting the nominal distance–power loss law, the strayed nodes estimate their distance from each beacon. Then, each strayed node draws a pair of horizontal lines and a pair of vertical lines around each beacon, in such a way that the minimum distance between each line and the beacon position equals the estimated node–beacon distance. The node localizes itself in the center of the rectangular area obtained by considering the innermost horizontal and vertical lines, that is to say, the lowest and highest among all the horizontal lines placed above and below each beacon, respectively, and the leftmost and rightmost among the vertical lines placed on the right– and left–hand side of each beacon. Intuitively, the smaller the intersection area the better the localization, though a certain error is unavoidable, even in the presence of perfect ranging.

Multilateration

Multilateration [10, 11] is a simple range-based, decentralized localization algorithm, based on geometry principles. As usual, strayed nodes collect the beacon messages and estimate their distance to each beacon. Then, any strayed node computes its own position by intersecting the circles centered on the positions occupied by the beacons and having radius equal to the estimated distance between the beacons and the node itself. Ideally, the intersection should be a single point on a surface, but due to channel and environment impairments, this intersection identifies an area where the node is likely to be found. In practice, the environment can be represented by an occupancy grid quantized in cells of finite size (a few centimeters). Each cell is given a weight equal to the sum of the squared distance between the cell and each circle. The node is then positioned in the center of the cell with lowest weight. Multilateration is slightly more complex than Min–Max but, at least in principle, it provides better performance, implementing a more sophisticated localization technique.

Maximum Likelihood

The *Maximum Likelihood* (ML) [5, 12] localization technique is based on classical statistical inference theory. Given the vector of RSSI values $\rho = \{\rho_\mathbf{1}, \rho_\mathbf{2}, \ldots \rho_\mathbf{n}\}$ obtained from n beacons with coordinates $\mathbf{x_B} = \{x_{B,1}, x_{B,2}, \ldots, x_{B,n}\}$ and $\mathbf{y_B} = \{y_{B,1}, y_{B,2}, \ldots, y_{B,n}\}$, the algorithm computes the a priori probability of receiving ρ for each potential position $[x, y]$ of the strayed node. The position that maximizes the probability is then selected as the estimated node position.

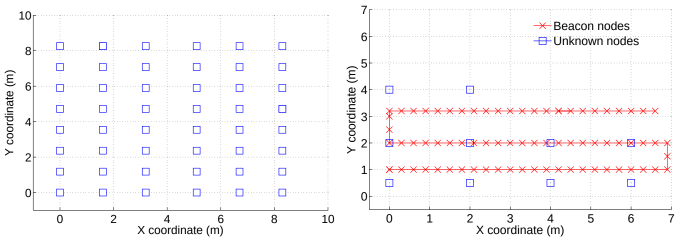
The Maximum Likelihood method is much more complex than the others, but it minimizes the variance of the estimation error as the number of observations, i.e, of reference beacons, grows to infinity. Unfortunately, in most realistic scenarios the number of beacons is very limited, so that the ML performance can be rather unsatisfactory.

ROCRSSI

ROCRSSI, originally proposed in [13], is a range–free algorithm that only relies on the assumption that the received power is a decreasing function of the distance between transmitter and receiver. The algorithm requires every anchor node to periodically broadcast a vector containing the RSSI of the packets received from the other beacons. Strayed nodes collect these RSSI vectors, together with the power that they receive from the anchors, storing the data in their memory. After collecting enough measurements, a strayed node can start the localization process. For each anchor node, say A, the strayed node X compares the power it has received from A, ρ_{AX}, with the power that other anchor nodes, say B and B', has received from A, ρ_{AB}, $\rho_{AB'}$. Based on this comparison, it determines whether it lies inside our outside ρ_{AB} and ρ'_{AB}, thus determining a ring centered in A where the node is likely to be located. The procedure is repeated for every other in–range pair of anchors and the node is finally located in the middle of the region where the largest number of rings intersect.

3 Testbed

In this section we present the experimental scenarios. We used IFX-Eyes sensor nodes, which have been extensively used by our research group to test protocols and algorithms for classical Wireless Sensor Networks (WSN) [14, 15]. The nodes can be programmed and powered via USB, thus permitting easy interconnection with other digital devices. Each board is equipped with a radio interface that provides 19.2 kbps transmission rate by using FSK



(a) Testbed #1 (b) Testbed # 2

Figure 1. Topology of testbeds

modulation in the 868.3 MHz band. The platform is also equipped with light and temperature sensors. Furthermore, a *Received Signal Strength* (RSS) circuit returns a two-byte integer proportional to the received signal strength, i.e., the so-called RSSI.

The experiments have been performed in two different testbeds, whose topology is sketched in Fig. 1. The entire set of collected measurements can be downloaded from the SIGNET group website [16].

Testbed #1

The first testbed consists of a room measuring approximately 10×10 meters in which we deployed 48 EyesIFX nodes. The nodes are placed on a grid and suspended at approximately 75 centimeters from the ceiling. Furniture and people present in the room cause the radio channel to be time varying and highly affected by multipath interference.

Testbed #2

The second testbed consists of a WSN composed of a dozen of EyesIFX sensor nodes and of a mobile node [17] that is assumed to be always aware of its own position, being able to provide an arbitrary number of virtual beacons to the static nodes in its coverage area.

4 Channel Characterization

Our first goal is to determine a suitable radio channel model for our environment. We consider a simple path loss channel model, in which the generic i–th node, placed at distance d_i from the transmitter, receives a signal with power P_i (in dBm) given by:

$$P_i\,[dBm] \;=\; P_{loss}(d_i) \;+\Psi_i+\alpha_i(t)\,; \tag{1}$$

where

$$P_{loss}(d_i) \;=\; P_{Tx} \;+K-10\eta\log_{10}\left[\frac{d_i}{d_0}\right]\;. \tag{2}$$

In the previous equations, P_{Tx} is the nominal transmission power (in dBm), K is a unitless constant that depends on the environment, d_0 is a reference distance for the antenna far field, and η is the path loss coefficient. The term Ψ_i denotes the random attenuation due to shadowing, while $\alpha_i(t)$ accounts for the fast fading effect [18]. Typically, shadowing is almost constant over long time periods, while fast fading shows rapid fluctuations, so that packets received in different time epochs likely experience equal shadowing, but almost independent fading.

The fast fading term in (1) can be averaged out by considering multiple readings from the same static node. Thus the channel model can be simplified as follows

$$P_i\,[dBm] \;\simeq\; P_{Tx} \;+K-10\eta\log_{10}\left[\frac{d_i}{d_0}\right]+\Psi_i\,. \tag{3}$$

Medium–scale shadowing effect, however, cannot be easily eliminated when both transmitter and receiver are stationary. The statistical distribution of this factor is generally assumed to be Gaussian, with zero mean and variance $\sigma^2_{\Psi_i}$ whose value ranges from 4 up to 12 depending on the characteristics of the environment [18]. Furthermore, the shadowing process generally presents spatial correlation, although in this study we will assume the shadowing terms to be independent and identically distributed.

We adopted a Mean Square Error criterion to determine the path loss model parameters K, η and d_0, as given in (2) for each testbed, from the received power samples collected in each scenario. The result for scenario #1 is shown in Fig. 2, where the dashed line refers to the empirical data, the solid line corresponds to a pure path loss model with parameters $P_{Tx}+K=-30.5$ dBm, $\eta=1.64$, $d_0=1$m and the circles represent measurement samples. As it can be observed, the fitting is fairly good.

According to (3), the difference between the theoretical received power given by the pure path loss model (2) and the measured values is the shadowing term Ψ_i. The quantiles of such a difference are plotted in Fig. 3 versus the quantiles of a standard Normal distribution. The QQ–plot reveals that, as expected, the error samples distribution is fairly close to a Normal distribution, whose standard deviation can be estimated from the empirical samples as $\sigma_\Psi=6.82$ dB.

Tab. 1 reports the estimated parameters for the two scenarios.

Table 1. Channel parameters estimation on testbed #1 and #2

Scenario	$K+P_{Tx}$	η	σ_Ψ
#1	-44 dBm @1m	1.64	6.82 dB
#2	-45 dBm @1m	1.51	6.34 dB

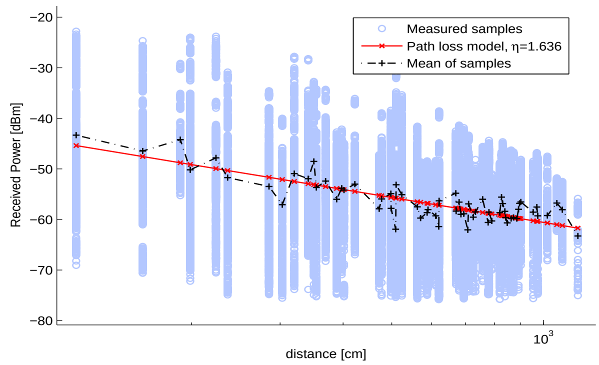


Figure 2. Channel parameters estimation on testbed #1

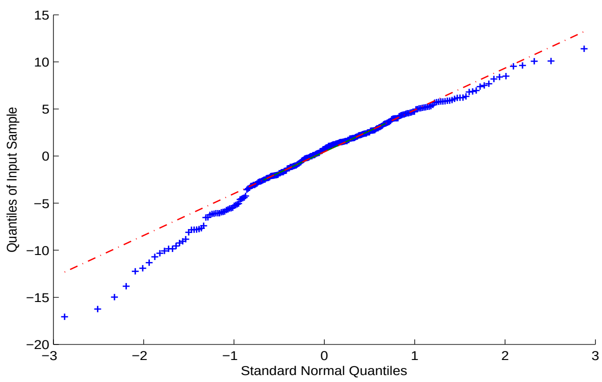


Figure 3. QQ–plot of the residuals

It might be worth remarking that the estimation of the distance obtained by inverting the path–loss model given by (2) is biased.

In fact, denoting by d_{true} the real distance between transmitter and receiver, we have

$$\hat{d} = d_0 10^{\left(\frac{P_t+K+\psi-P_r}{10\eta}\right)} = d_{true} 10^{\frac{\psi}{10\eta}}. \quad (4)$$

Taking the expectation of $\hat{d}$ we get

$$E[\hat{d}] = d_{true} E[e^{\frac{\psi log10}{10\eta}}] = d_{true} e^{\frac{1}{2}\left(\frac{\sigma_\psi log10}{10\eta}\right)^2}$$

where the right-most term represents the bias coefficient. Since the bias is independent of the position of the nodes and of the received power, it can be compensated as follows [5]:

$$\hat{d}' = \hat{d} \cdot e^{-\frac{1}{2}\left(\frac{\sigma_\psi log10}{10\eta}\right)^2}.$$

5 Results

In this section we show the experimental results obtained running the different localization algorithms presented in Sec. 2 in the two scenarios described in Sec. 3. The aim of this analysis is to explore how the localization precision is affected by the number of anchor nodes and by the specific algorithm used.

Fig. 4 shows a map of the variance of the ML localization error in an area corresponding to the Testbed #1, for a fixed deployment of six beacons. The color of each cell corresponds to the average value of the localization error observed in that cell. Notice that, unlike in the other graphs reported in this paper that always refer to empirical data, the results shown in Fig. 4 have been obtained by simulating different realizations of the radio channel, according to the parameters reported in Tab. 1. Observing the results reported in the figure, we cannot conclude much about the dependence of the localization error on the beacon positions. As expected, localization error tends to reduce in proximity of the beacons, although this not always true. Conversely, the cells close to the room corners experience larger localization errors, probably due to the worse multipath effects. However, the behavior of the localization error in indoor environments is quite unpredictable.

In Fig. 5 and Fig. 6 we report the average localization error, defined as the distance between actual and estimated position, obtained using the different algorithms in the first and the second testbed, respectively. Notice that in Testbed #2 we have moved a single anchor node in several different positions (each corresponding to a *virtual* anchor), so that we cannot apply the ROCRSSI algorithm that requires RSSI measurements between different pairs of anchors. The results are represented with their statistical confidence intervals, which grow when the number of anchors increases. In fact, the statistical confidence of the results depend on the number of different scenarios that could be extracted from our testbed deployments. Therefore, the larger the number of anchor nodes, the lower the number of different topologies that could be extracted and, consequently, the lower the statistical confidence of the results.

As a first thing, we can notice that the performance obtained by the different algorithms in the two environments is qualitatively comparable, with ML outperforming all the other algorithms when the number of anchor nodes is equal to 7 or more. When the number of anchor nodes is less than 7, however, the other algorithms yield comparable or even better performance. It should be noted that the ML algorithm has a much higher computational cost than the other schemes here considered, and it requires a good characterization of the radio channel, including the standard deviation σ_Ψ of the shadowing term. The Min-Max scheme, on the contrary, is much less demanding in terms of computational cost and does not require the characterization of the shadowing term. Unfortunately, the Min-Max performance does not improve significantly by increasing the number of anchor nodes. In fact, the scheme presents a performance floor that apparently depends on the considered environment.

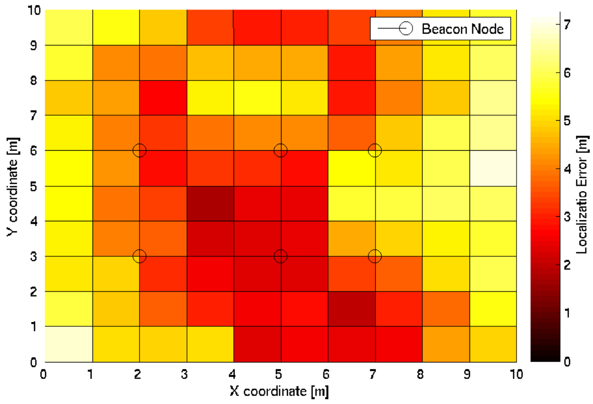


Figure 4. Localization error map (simulated)

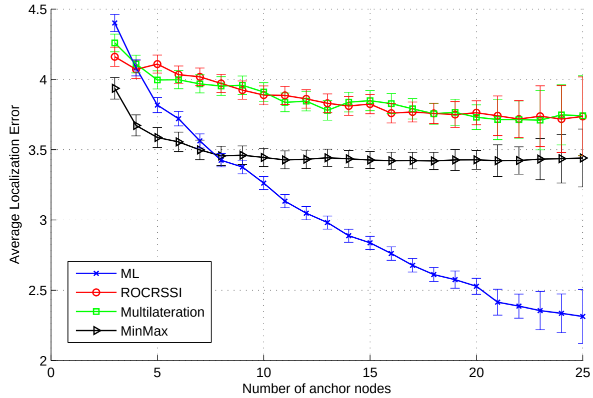


Figure 5. Localization error in Testbed #1

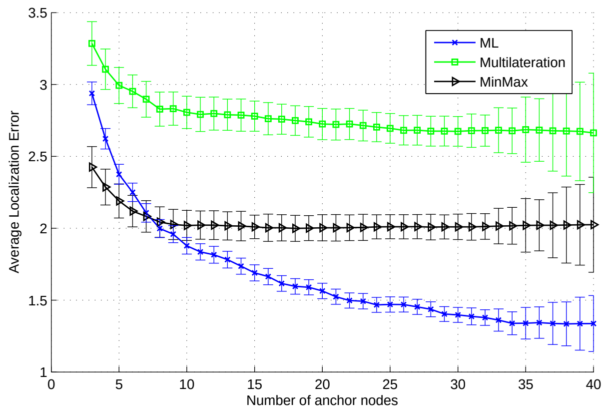


Figure 6. Localization error in Testbed #2

The performance of the ROCRSSI and multilateration algorithms are comparable, and generally worse than the other schemes. However, ROCRSSI offers the advantage of not requiring any radio channel characterization. In general, for the same number of anchor nodes, the performance obtained in Testbed #2 is better than that achieved in Testbed #1. This indirectly confirms that the presence of furniture and moving people exacerbates the RSSI–based localization problems.

Finally, Fig. 7 shows the cumulative distribution function (CDF) of the localization error obtained in Testbed #1, using the ML and Min-Max schemes, with 5, 15, 25 and 35 beacons. It is interesting to observe that the CDF curves of ML grow more smoothly than those of Min-Max. In other terms, the localization errors obtained by adopting the ML algorithm span from a few centimeters to a few meters, whereas the Min-Max algorithm tends to concentrate

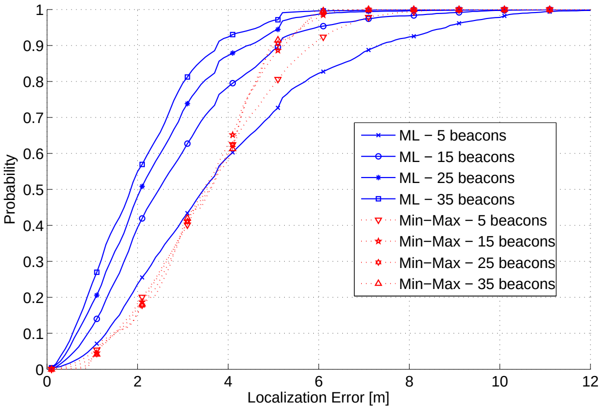


Figure 7. Cumulative distribution function of the localization error on Testbed #1

the localization errors in a smaller region. This is probably due to the well known tendency of Min-Max to shift position estimates towards the center of the network [11], thus limiting the estimation error to half of the room side.

6 Conclusions

In this paper we analyzed the behavior of various localization algorithms, namely ML, Min-Max, Multilateration and ROCRSSI, using real data from two different scenarios. We show that the ML algorithm yields better performance than the others when the number of anchor nodes is relatively high. The main reason is that ML is the only algorithm that weighs the RSSI from the anchor nodes according with the reliability of such a reading, which decreases with the received power. However, the performance obtained in our testbeds are still rather unsatisfactory, with localization errors comparable with the room side. Multilateration is much simpler than ML, though it achieves even worse performance. The same considerations hold true for ROCRSSI, which however offers the advantage of being independent of the channel parameter estimates. Finally, Min-Max seems to offer a good compromise, having a very low computational cost and offering better results than multilateration and ROCRSSI. However, the relatively good performance achieved by the Min-Max algorithm is mainly due to its tendency to localize the strayed nodes in the center of the area, thus limiting the distance error to half of the maximum distance between the two farthest locations in the considered area.

In conclusion, RSSI-based localization in indoor environments presents severe limitations. An accurate radio channel model might alleviate these problems, though the presence of moving people or obstacles would further exacerbate the situation. Therefore, in most common indoor scenarios, RSSI-based localization schemes do not appear suitable to provide accurate localization (with errors limited to few centimeters) by leveraging on only a limited number of beacons deployed in the area.

7 References

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