SMARTPOS: Accurate and Precise Indoor Positioning on Mobile Phones

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***Abstract*—Location-based services are possibly the most popular services with respect to mobility, since they allow for the automated filtering of information relevant to the user. This paper presents a detailed evaluation of SMARTPOS, an indoor positioning system based on deterministic 802.11 fingerprinting and a digital compass. SMARTPOS is accurate enough to supply location estimates for indoor location-based services and can be deployed standalone on a mobile phone. The system considers the user's orientation to avoid errors caused by the blocking effect of the human body. For location estimation it takes only that part of the fingerprint database into account that corresponds to the user's current orientation. SMARTPOS achieves a mean position error of 1.16 meters and a maximum position error of 2.74 meters in a 250 square meter environment.**

***Keywords*-Location Systems, 802.11 Fingerprinting, Mobile Phone Positioning, Location-Based Services.**

I. Introduction

In recent years, a trend towards mobility can be recognized. Smartphones, small devices with comparatively high processing power and mobile internet, make it possible to work while traveling, to stay connected to social networks, and to retrieve nearly any information anywhere at any time. One of the most popular mobile services are location-based services (LBS). These are value-added services, which utilize the location of the mobile to present the user with information about its surroundings. Navigation and information services, friend-finder, pet-tracker, and location-based games are only a small part of the number of services and applications filling the app-stores of the world.

The key enabler for LBS is the Global Positioning System (GPS) [1]. It enables accurate positioning in outdoor environments, the usage is free of charge, the system is globally available, and most of today's smartphones are equipped with a GPS-receiver. Unfortunately, GPS is not able to track people in indoor environments with acceptable accuracy. Signals might get lost due to attenuation effects of roofs and walls or lead to position fixes of very low accuracy due to multipath propagation.

Even worse, indoor location-based services require much higher precision guarantees than outdoor services. Errors should not exceed a few meters to allow for a differentiation between several floors or rooms. Otherwise, the service could provide information for places, which are quite far away from the actual position of the target. Despite these challenges many users would appreciate indoor location-based services, especially in large and complex buildings such as museums, shopping malls, airports, hospitals, or university buildings.

Existing indoor positioning techniques can be grouped by their level of precision and the expenses for additional infrastructure. Dedicated indoor positioning systems such as ultra wide band or ultrasonic systems consist of several components with the sole purpose of determining the positions of possibly multiple targets in indoor environments. The precision is often high, but an expensive infrastructure is needed and hence the space where positioning is possible is usually limited to a small area, where higher accuracy compensates the high cost. Another class of systems is built on existing infrastructure such as WLAN, Bluetooth or inertial sensors for positioning. The precision of such systems is limited, but the system can be deployed with few additional expenses.

In this paper, we present SMARTPOS, an indoor positioning system for smartphones based on deterministic WLAN fingerprinting and a digital compass. The system is self-positioning, meaning that the whole positioning process (including all measurements) is carried out on the phone. It achieves a high accuracy within few meters and therefore is able to provide indoor location-based services with high quality location estimates at no additional expenses. SMARTPOS makes use of the user's orientation to avoid errors caused by the blocking effect of the human body. Only those fingerprints are considered for location estimation that were measured while viewing in a similar direction like the user.

The remainder of this paper is structured as follows: In the next section, a short overview of existing indoor positioning systems is given. In Section III, SMARTPOS is presented in detail while in Section IV, the impact of several parameters is analyzed and discussed. Weighted and non-weighted kNN (k-nearest neighbors) in signal space, the influence of missing values on the algorithm and the performance gain of including the orientation on SMARTPOS and a Naive Bayesian Estimator are evaluated. Section V concludes the paper and gives hints on future work.

II. Related Work

In the past 15 years, a variety of technologies for indoor positioning have been proposed. A good overview of existing indoor positioning systems using radio frequency (RF) technologies such as radio frequency identification (RFID), ultra wide band (UWB), ultra high frequency (UHF), WLAN and Bluetooth is given in [2]. However, they do not describe up-to-date systems, which have been developed since 2007. We therefore focus in this section on the recent development and work closely related to our research.

Many state-of-the art systems rely on fingerprinting algorithms [3], [4], [5], [6]. These algorithms work in two phases: The first phase, the offline phase, is used to collect signal strength measurements (the fingerprints) from access points throughout the building at predefined reference positions. In the second phase, the online phase, the signal strength information is continually measured and compared to a database of all fingerprints from the offline phase. Different algorithms calculate the position as the nearest fingerprint in signal space, the average of the k-nearest neighbors with or without the distance in signal space as additional weight or utilize probabilistic methods. Localization techniques based on fingerprinting can be divided into two classes: deterministic and probabilistic techniques.

Deterministic systems compute the location estimate as a function of the received signal stregth (RSS) values measured using a physical model incorporating the values stored in the fingerprint database. One of the first systems working with WLAN fingerprints to retrieve a position estimate is the RADAR system [3]. RADAR is a deterministic system that utilizes kNN for position estimation and offers an optional signal propagation model for the automated creation of the fingerprint database. The authors noticed already the impact of the user's orientation and proposed obtaining empirical data for multiple orientations. Kaemarungsi et al. analyze the effects of the user's presence and orientation on RSS values in [7]. The results show that the attenuation effects of the human body can lower the RSS by more then 9dBm.

Probabilistic techniques [4] on the other hand compute a distribution based on the measurements from the offline phase and use probabilistic techniques to estimate the user's position. COMPASS [5] is one of the first probabilistic indoor positioning systems that adresses the problem of attenuation effects caused by the human body by adding a compass to the system. In the offline phase, fingerprints for several selected orientations (typically each $45°$ or $90°$) are collected at reference positions. In the online phase, the user's orientation is calculated by a digital compass and only the fingerprints with a similar orientation are used for the positioning algorithm. COMPASS presents the most similar approach to our system. However, we additionally analyze the impact of orientation information for deterministic techniques as well as for a bayesian approach. We also compare our results with a system not filtering the orientation information and thus benefiting from a much larger database. Chan et al. also present a system running on a mobile phone considering the orientation of the user in [8], but apply a technique called Newton Trust Region for further position refinement. Martin et al. present one of the first WLAN positioning systems, which integrates both offline and online phase on a mobile phone [9].

Most up-to-date systems combine WLAN fingerprinting with additional technologies such as inertial sensors to offer more accurate position estimates and continuous tracking functionality [10]. The authors utilize a particle filter for fusing WLAN fingerprint location estimates with an accelerometer.

III. SMARTPOS: A System for Self-Contained Mobile Positioning

In this section, we describe SMARTPOS, a system for an accurate and self-contained indoor positioning based on deterministic 802.11 fingerprinting and a digital compass. The system runs stand-alone on a mobile phone and consists of a management module for the creation and maintenance of the fingerprint database and a module for location determination. The latter offers the possibility of modifying several parameters concerning the deterministic location estimation or allows a change of the positioning method to a room-based bayesian approach.

A. Database Creation on a Mobile Phone

During the offline phase, active scans for WLAN signals from surrounding access points (APs) are executed with a mobile phone at several reference positions. The measured signal strength values are enhanced with the viewing direction and the pixel coordinates of the reference position on a bitmap of the floor. The viewing direction is obtained by the digital compass of the smartphone, the position is assigned by tapping on a zoomable and scrollable map displayed on the screen of the mobile. Finally these values (in the following referred to as fingerprints) are stored in a database. At each reference position, four fingerprints are created, one in the direction of each axis of the specific building. The alignment along the axes of the building instead of the geographic directions is carried out to improve the accuracy of the application in tracking scenarios since most users move along the main axes of a building, e.g., when walking down a corridor. For each fingerprint, five scans are executed and the average of the received signal strengths is stored in the database to reduce the impact of short-time fluctuations. Furthermore, the orientation of the phone, which is derived from the mobile phone's compass, is averaged throughout the sampling time and also stored in the database. This is done to remedy the disturbances of the magnetic field inside of buildings, especially near electronic sources or large amounts of metal.

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B. Deterministic Location Estimation

During the online phase, SMARTPOS utilizes a deterministic positioning algorithm based on weighted kNN to estimate the approximate position of the user. WLAN signal strength measurements are carried out in a continuous fashion and for each measurement m the current orientation o of the phone is measured by its digital compass.

The orientation is considered to represent the approximate viewing direction of the user and hence implicitly yields the information about the attenuation of his body. The online RSS values should therefore not be compared to all fingerprints in the database due to possible influence of the human body, but only to those fingerprints that correspond to a similar viewing direction to o during the offline phase. Since the viewing direction is retrieved from the noisy readings of the compass, the orientation is averaged over the duration of each scan. This mechanism could also be replaced by advanced filtering algorithms to reduce the impact of outliers. SMARTPOS considers only a subset S of all fingerprints in the database containing those with a maximal deviation of 50° from o and is therefore able to reduce the number of fingerprints matched in the online phase to an extent of 25% of the database size.

On the remaining subset S of filtered fingerprints, the nearest neighbours in signal space with respect to m are computed. SMARTPOS uses a sophisticated distance metric for the comparison of two RSS measurements (i.e., the online measurement m and a fingerprint $f \in S$): Each measurement contains the information about all RSS values with the mac adress of the AP, which sent the signal. Since at a given position only signals of a subset of all access points in the building can be received, the question arises how to treat missing signal strength imformation in one of two compared measurements. One possibility would be to assign a fixed value MIN to the RSS of all access points missing in one measurement. This mechanism favors combinations of measurements, where signals by an AP are of very small strength in one measurement and missing in the other instead of combinations, where a high RSS value in one measurement is missing a counterpiece in the other. The value of MIN should be below the minimal RSS value measureable by the device. The other possibility is to ignore all signal strength information missing at least in one of the compared measurements. Based on the results of a detailed evaluation (see Section IV) SMARTPOS utilizes the second approach, which is expected to be more robust in the case a new AP is turned on or an existing AP is turned off.

Based on the Euclidean distance $d_i = dist(m, f_i)$ in signal space the subset $N \subset S$ of the k nearest neighbours is computed. In addition SMARTPOS assigns a weight w_i to each fingerprint $f_i \in N, i \in \{1, \dots, k\}$ according to the following formula:

$$w_i = \left(d_i \sum_{j=1}^{k} \frac{1}{d_j} \right)^{-1} \tag{1}$$

It is easy to see that the w_i are normalized since $\sum_{i=1}^{k} w_i = 1$. For the computation of the user's position l, SMARTPOS calculates the weighted average of $l_i, i \in \{1, \dots, k\}$, l_i being the reference position of the fingerprint f_i:

$$l = \sum_{i=1}^{k} l_i w_i \tag{2}$$

C. A Naive Bayesian Location Estimator

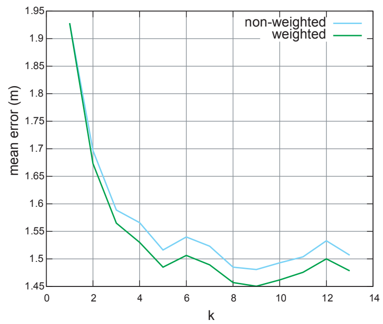
A Naive Bayesian Estimator is a simple and still very powerful classification scheme. The main ingredient is Bayes theorem, which is used to infer the probability $P(I|M)$ of an event I conditional on a measurement M. Using Bayes rule, we can turn over I and M and calculate from the probability of measuring M in the case that we are inside a given room I.

$$P(I|M) = \frac{P(M|I)P(I)}{P(M)} \tag{3}$$

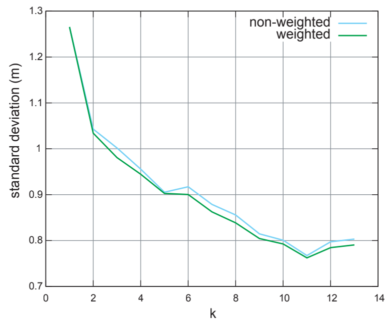
The probabilities on the right hand side are estimated from a labelled set of instances simply by counting or calculating the mean and variance of each one-dimensional parameter and assuming a normal distribution. This trick assumes that the parameters are statistically independent. As this is usually not true, the performance of a classifier on a given problem has to be carefully estimated. It is common to use a method called cross-validation for measuring the quality of a classifier. This is done by splitting the training data and using a majority for training and holding back a minority to calculate a success rate on this test set. The details of how to do this and the basic caveats can be found in many textbooks on data mining.

IV. Evaluation

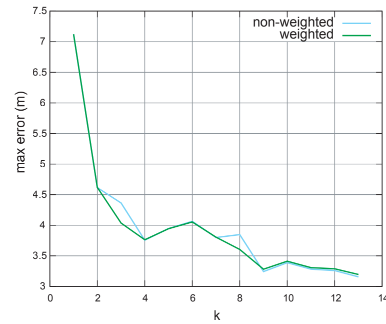
For the evaluation of our system, we created two sets of fingerprints in a part of our university building. All RSS information was gathered with a HTC Desire. The first set is arranged in an approximate grid of 79 reference positions with fingerprints measured in the direction of all four main axes of the building, which results in 316 fingerprints in total (the grey dots in Figure 1). The second set is a much smaller set of 64 fingerprints at 16 pseudo-randomly distributed reference positions (again measured in the direction of all four axes) within the coverage of the database and is used as substitution for online measurements (the black dots in Figure 1). This ensures that our results originate from an identical setting for all the different location estimators. The estimators are evaluated in respect to four criteria



(a) The mean error in meter



(b) The standard deviation in meter



(c) The maximum error in meter

Figure 2: Comparison of weighted and non-weighted kNN

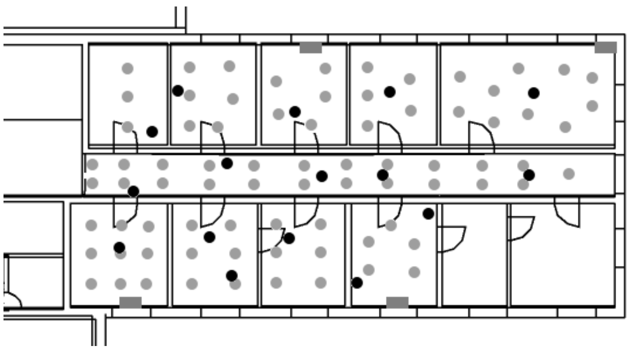


Figure 1: Reference database (gray dots) and online testset (black dots). APs are displayed as grey rectangles.

according to [2]: the accuracy as the mean position error, the precision as the maximal and the standard deviation, and the complexity as the number of compared fingerprints. The question of scalability, cost and robustness is not considered, since the scalability and the cost are the same in all systems and the robustness is hard to measure. In the following the results from a detailed evaluation of SMARTPOS in the described setting are presented and discussed. SMARTPOS is evaluated as follows: First the deterministic kNN approach is analyzed and the settings of several parameters compared to each other. The questions of assigning a weight to the nearest neighbors and whether missing signal strenght imformation should be considered or ignored are discussed and the impact of the user's orientation on accuracy and precision presented. In a consecutive step an optimal value for k is determined for SMARTPOS. Finally, the usage of orientation information in a Naive Bayesian Estimator is analyzed.

A. *Weighted or Non-Weighted kNN*

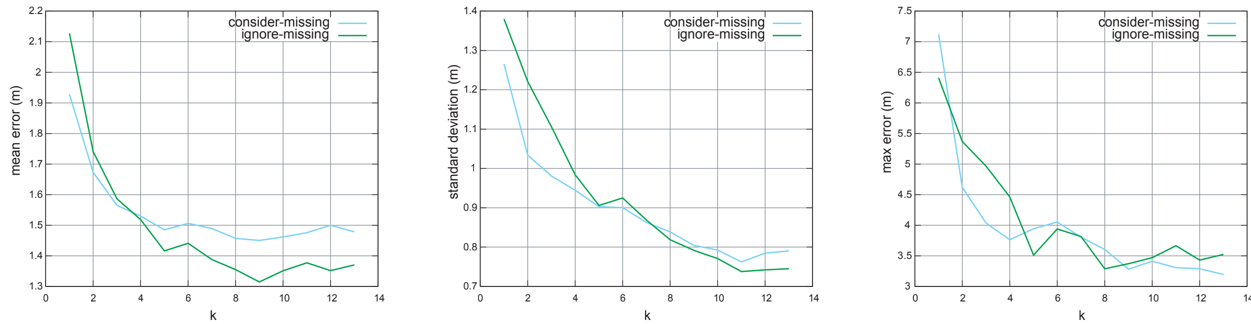
When using a kNN approach together with WLAN fingerprinting one has to decide whether just to compute the center of the nearest neighbors or to add a weight to each of the k-nearest neighbors according to the distance in signal space and then calculate the center of mass. With SMARTPOS, we evaluated both approaches for variable k. Figure 2 shows the results. The weighted approach behaves similarly, but performs better for each $k > 1$. The same applies for the deviation while the maximum error shows no significant difference except for two outliers ($k = 3$ and $k = 8$), for which the weighted approach also performs better. SMARTPOS therefore utilizes a weighted kNN as described in Section III-B.

B. *Treatment of Missing RSS*

In Section III-B, two approaches for the treatment of missing signal strength information when comparing two RSS measurements are described. One considers the information by assigning a minimal value of -100dBm for the missing RSS information, the other ignores all RSS values from APs measured only in one of the two compared measurements. Both approaches were tested for a variable k and the results are presented in Figure 3. The accuracy of a system ignoring missing values is higher than the accuracy of a system considering the information for each $k > 3$ and also offers a minimum mean error for $k = 9$. The deviation only becomes smaller for each $k > 7$ with the minimum for $k = 11$, while the maximum error oscillates and therefore adds little information. Hence, SMARTPOS ignores missing RSS values.

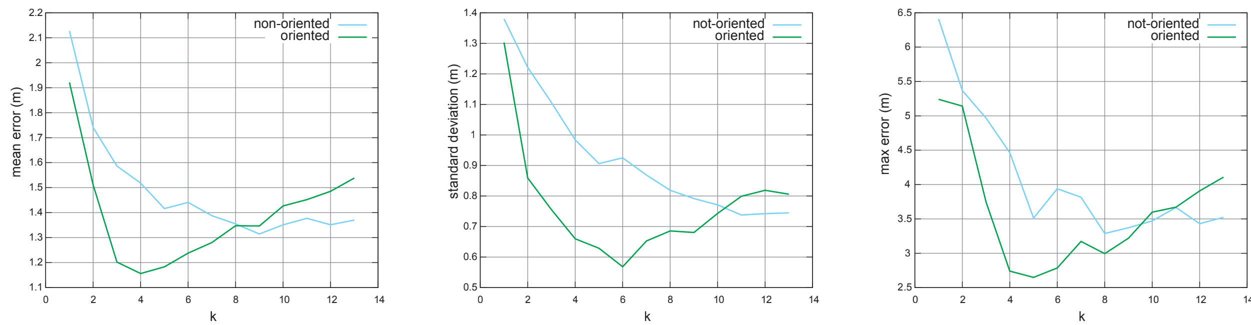
C. *Impact of Orientation Information*

The most profound innovation of SMARTPOS is the usage of orientation information in a deterministic location estimation system on a smartphone. With the filtering of the fingerprints in the offline database with respect to the orientation information of the user, the compexity of the online matching can be quartered (when using the state of the art four directions for each reference position) and the accuracy and precision increased by a considerable amount. Figure 4 shows the results of the tests. The mean error is much smaller when using the orientation information and also reaches its minimum of 1.16m for $k = 4$, while the approach without orientation information reaches its minimum of 1.31m for $k = 9$. The minimal deviation of 0.57m for



(a) The mean error in meter (b) The standard deviation in meter (c) The maximum error in meter

Figure 3: Comparison of considering and ignoring missing RSS values



(a) The mean error in meter (b) The standard deviation in meter (c) The maximum error in meter

Figure 4: Comparison of considering and ignoring the user's orientation

$k = 6$ is also much smaller than the minimal deviation of 0.74m for $k = 11$ without considering the orientation. The same is true for the maximum error, which is minimal for $k = 5$ with a value of 2.65m when considering the user's orientation, whereas without the orientation information the minimum is 3.29m for $k = 8$. The much smaller number of k when using the orientation approach can be explained by the fact that the number of fingerprints for comparision is quartered and each online measurement has at most 4 neighbors in the grid, while without the filtering of the user's orientation the number of neighbors can increase to a total of 16 neighbors, because 4 fingerprints are stored for each reference position. In conclusion SMARTPOS utilizes the orientation information of the user to improve accuracy and precision of the location determination, while reducing the complexity at the same time.

D. Determination of k

Based on our experiments with SMARTPOS, we recommend utilizing an orientation-based weighted kNN approach with $k = 4$. For the comparison of measurements one should ignore all signal strength information of each AP missing at least in one of the measurements. With these parameters, the system offers the lowest mean error of 1.16m of all possible combinations with an acceptable deviation of 0.66m and a small maximum error of 2.74m.

E. Orientation and the Naive Bayesian Esitmator

The influence of filtering fingerprints according to their orientation on deterministic kNN positioning has been described. To get a deeper understanding of what influence the reduction of the search space according to the viewing direction has on indoor positioning, we chose to evaluate on the most simple (and often most effective) way of inducing a position from given measurements: Assuming that the variance in measurements is normally distributed, we estimate the mean and variance of a set of measurements taken in the same room and reuse this information for identification.

In order to do so, we assigned a label with each fingerprint specifying the room that it lies in. The long corridor has been cut into three rooms to reduce the variance of measurements in this long area as depicted in figure 5. Using this labeled data, we constructed a Bayesian Estimator, which calculates for each pair of access point and label the mean, standard deviation, weight sum and precision and reuses them for classification. We tested the classification performance with 10-fold stratified cross-validation training on 90% and evaluation on the remaining 10% of the data.

We used this technique on five different datasets: A dataset for each quadrant and a dataset where a random subset of 25% of all measurements in all directions were taken. In this

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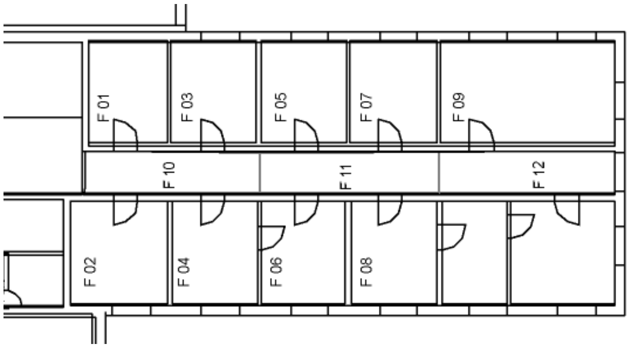

Figure 5: Labeled rooms for the Naive Bayesian Estimatior.

Table I: Evaluation results

Dataset	Number of Fingerprints	Success Rate
All directions	78	79%
North	72	62.5%
West	77	70.13%
East	82	65.85%
South	82	71.95%

way we achieve comparable training set sizes.

The results from this experiment are negative: A Bayesian classification of room-labels performs better on the total set of measurements than on the direction-dependent subsets. The results are given in Table I. Hence, for a system based on Bayesian estimation theory, we propose not to use the direction as a filter.

V. Conclusion and Future Work

In this paper, we presented SMARTPOS, a positioning system on a smartphone based on deterministic WLAN fingerprinting and a digital compass. SMARTPOS utilizes a weighted kNN approach with $k = 4$ and with a distance metric in signal strength space, which ignores RSS values from access points visible only at one fingerprint. We analyzed the impact of several parameters and conclude that a weighted approach results in more accurate and precise results than a non-weighted approach. Ignoring missing RSS values provides better results than assigning a minimal value, at least for higher values of k. In our setting this was the case for $k > 3$ in the oriented approach and for $k > 7$ in the approach without the user's orientation. With adding the user's orientation, SMARTPOS is able to reduce the mean positioning error to 1.16m and the variance to 0.66m. The maximal error in this case is 2.74m, which is 55cm smaller and therefore much better than the minimal maximum error of 3.29m in all experiments without the orientation information. We conclude that the user's orientation should be considered in deterministic 802.11 fingerprinting. However, we also discovered that the orientation information should not be used as a filter in a Naive Bayesian Estimator, since the percentage of correctly recognized rooms was smaller than that of the same algorithm trained with a similar large set of data containing fingerprints of all viewing directions.

In the near future, we want to expand the mechanism for filtering the database for faster access by including an accelerometer to the system. We hope that after an initial position fix we are able to further reduce the candidate set and can therefore support even large databases (e.g., at airports) standalone on the phone. Furthermore, we are currently working on mechanisms for a self calibrating system to replace the cumbersome process of keeping the fingerprint database up-to-date.

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