

Hybrid Fusion Approach combining Autonomous and Cooperative Detection and Ranging methods for Situation-aware Driver Assistance Systems

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Abstract—Current driver assistance systems such as Adaptive Cruise Control (ACC) and in particular future assistance systems such as Collision Warning make high demands on reliability of detection and ranging methods for vehicles within the local vicinity. Autonomous systems such as Radar which are already integrated into a multitude of vehicles meet these requirements to only a limited extent. As an alternative, cooperative systems for detection and ranging will be enabled by future Vehicle-2-Vehicle communication. But cooperative detection and ranging also has drawbacks regarding reliability due to positioning and transmission errors if it is applied in a standalone way.

Thus, the solution presented in this paper is a hybrid approach combining autonomous and cooperative methods for detection and ranging within a common architecture. A particle filter is used for state estimation. The results are a higher detection effectiveness and a lower position error compared to using standalone autonomous or cooperative detection and ranging methods.

I. INTRODUCTION

Today, most traffic accidents occur due to a human false estimation of the current situation which is the consequence of misinterpretation or a limited amount and accuracy of information [1]. Future *Situation-aware Driver Assistance Systems* [2] will support humans in their task of driving a vehicle safely, efficiently and comfortably by exploiting situational information of the own vehicle as well as other information sources (other vehicles, road side units, etc). To reach this detailed situation awareness, information on the presence and position of vehicles in their local vicinity is of particular importance. Key enabler for future driver assistance is hence a complete and accurate model of their surrounding including each individual vehicle within the relevant scope because even having no or inaccurate information of a single vehicle may result in a perilous situation.

In order to gather information on the surrounding vehicles, methods for detection and ranging are required. Detection and Ranging (DaR) of objects means the determination of presence and position of these objects relative to the own vehicle, in the latter called ego vehicle. This information can then be used in a multitude of applications, e.g. Adaptive Cruise Control (ACC), hazardous following distance warning, frontal/rear-end/flank collision avoidance assistance, etc.

Objective of novel detection and ranging methods is to increase the *Detection Effectiveness* and decrease the *Position Error* at the same time. This paper will present a novel concept for a hybrid approach combining autonomous and cooperative detection and ranging.

Section II gives an overview of concepts and types of detection and ranging methods for vehicles. Causes of error that will play a major role for the proposed algorithm will also be detailed herein.

The proposed algorithm for a hybrid approach combining autonomous and cooperative detection and ranging methods is provided in section III. Initial simulation results are presented in section IV. The paper ends with a conclusion in section V.

II. DETECTION AND RANGING METHODS

In principle, two different types of detection and ranging methods have to be differentiated:

- **Autonomous detection and ranging:** Detection and ranging is performed only by the ego vehicle without active interaction of the target vehicle. The target vehicle stays completely passive.
- **Cooperative detection and ranging:** Detection and ranging is performed in a cooperative way by information provided by the target vehicle. The target vehicle plays an active role.

A. Autonomous Detection and Ranging

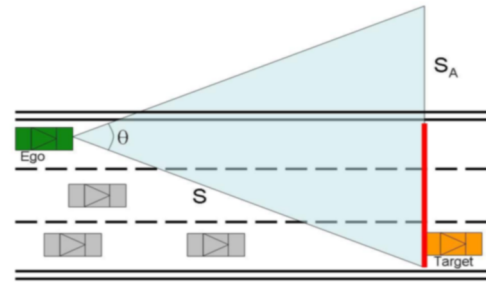


Fig. 1. Scenario

a) *Radar:* A common mechanism of autonomous DaR of objects is the measurement of transit times of electro-magnetic signals. This concept is exploited for instance by the well-established *Radio Detection and Ranging System (Radar)* which uses micro waves with a wave length of 1 millimeter up to several meters. Radar systems used as in-vehicle sensors work in the European regulative assigned frequency bands, i.e. the K-band at 24 GHz (until 2013 [3]) and W-band at 79 GHz (for future usage [4]) for Short Range Radar (SRR) applications and the W-band (76-77 GHz) for Long Range Radar (LRR) applications [5], [6], [7]. An essential parameter in the context

of Radar systems is the half-power beamwidth θ which depends on the above mentioned frequency f and therefore the wave length λ and the effective length of the antenna D and can be calculated by the equation [8]:

$$\theta = K \frac{c}{Df} = K \frac{\lambda}{D} \quad (1)$$

K is known as the beamwidth factor (e.g. $0.88(\text{rad}) \approx 50.76^\circ$ for uniform distribution rectangular apertures [9]). The angular resolution S_A of a Radar, which defines the minimum distance at which two equal targets at the same range can be separated, can be calculated by:

$$S_A \geq 2S \cdot \sin(\theta/2) = 2S \cdot \sin\left(\frac{K\lambda}{2D}\right) \quad (2)$$

S slant range

The Radar sensors available on the market today suffer from low angular resolution because of a half-power beamwidth of more than 6° due to aperture size limitations. According to Rasshofer et al. [10] this results in poor target separation in long and medium ranges. As an example, the angular resolution in a slant range of 150 meters according to equation (2) is more than 17m and thus spans at least over the two adjacent lanes with a lane width of 3,50m according to German standard cross-section RQ-33 [11] for a 6-lane autobahn (see fig. 1). An application such as ACC cannot adapt the optimal speed in this situation because it cannot infer whether there is one or more vehicles within the critical scope.

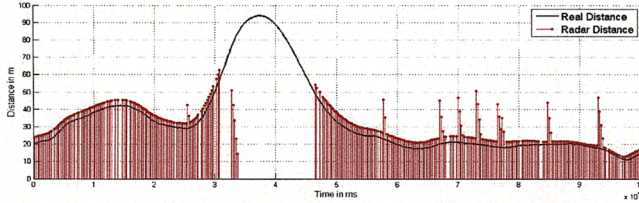


Fig. 2. Radar distance measurements

Modern Radar sensors use filter techniques to overcome the problem of poor angular resolution but show constantly significant measurements errors, target losses or "ghost targets" (see fig. 2). The figure shows Radar measurements (stems) recorded on a real test run. The real distance to the target vehicle is depicted as a solid line.

b) Lidar: Another autonomous DaR method which uses laser instead of microwaves is called *Light Detection and Ranging System (Lidar)*. Due to its high frequency, Lidar has a highly directional signal propagation and shows a much higher angular resolution. But, in contrast to Radar which do not show significantly deterioration in fog, rain or snow, Lidar sensors show high sensitivity towards these environmental influences.

B. Cooperative Detection and Ranging

In contrast to autonomous DaR methods, the target vehicle is actively involved in cooperative DaR. Therefore, the target vehicle cooperates with the ego vehicle by transmitting messages with position relevant data. By receiving the position relevant information, the ego vehicle can calculate the relative position of the target vehicle. So basically cooperative DaR comprises three steps:

- Self-positioning of both ego vehicle and target vehicle within a common reference system
- Transmission of the target vehicle's position to the ego vehicle
- Range calculation by the ego vehicle

These steps will be described more in detail in the following paragraphs:

a) Self-positioning: A promising solution for self-positioning is *Global Navigation Satellite System (GNSS)* because of its global availability in outdoor areas. Although GNSS is the most promising solution for positioning vehicles at present, other variants, e.g. GSM/UMTS signal measurements or dedicated road infrastructure, have to be mentioned as well but are not further studied in this paper. More information on self-positioning can be found in [12].

GNSS is based on lateration of unidirectional Time of Arrival (ToA) measurements and therefore several measurements from different satellites are required to get a complete position estimation. With elimination of impossible solutions at least two measurements to individual non-collinear satellites for a 2D positioning or three measurements for a 3D positioning are required. Normally, a further satellite is necessary for time synchronization between the space segment and the user terminal.

The ToA measurements of the user terminal can be based on two different levels:

- Code based measurements: ToA is measured on code level (synchronization on chip basis)
- Carrier based measurements: ToA is measured on carrier level (synchronization on carrier phase basis)

Sources for inaccuracy are up to delays in signal runtime resulting in erroneous pseudorange ρ calculation:

$$\rho = c\Delta t = c(\Delta\tau + \Delta\delta) = \varrho + c\Delta\delta \quad (3)$$

c is the velocity of signal propagation, $\Delta\tau$ is the theoretic signal transit time following line of sight, ϱ is the true geometric range and $\Delta\delta$ is the additional signal transit time that emerges due to satellite clock offset, satellite orbit dislocation, ionospheric and tropospheric refraction, receiver clock offset and multipath propagation. The former two error types, i.e. satellite clock offset and orbit dislocation, are specific to a certain satellite and only depend on this satellite. Atmospheric refraction errors depend on satellite and receiver position. Receiver clock errors and multipath errors strongly depend on the receiver and its local environment.

b) Position transmission: To inform the ego vehicle of position relevant data in time, the target vehicle requires a reliable communication channel which allows fast channel access and transmission times. Due to channel setup delays and infrastructure as prerequisite, cellular systems (e.g. GSM/UMTS) are suitable to only a limited extent. Preferable is ad-hoc networking with fast channel access schemes such as Vehicle-to-Vehicle (V2V) communication based on Wireless LAN.

WLAN based V2V communication is currently in the standardization process under *Wireless Access for Vehicular Environments (WAVE)* including IEEE 802.11p and IEEE P1609.1-4 in the U.S. and under ETSI TC ITS and the Car-2-Car Communication Consortium in Europe. Besides unicast and multicast as data distribution mechanisms geo-based anycast and broadcast addressing will be developed. CSMA/CA is used for medium access control which requires acknowledged message transmission for the detection of transmission errors as a result of packet collisions. In order to avoid the broadcast storm problem broadcasting is not feed back by acknowledgements and thus subject to unreliable message transmission. Packet loss strongly depends on the channel load which is influenced by the number of channel accesses, the message length and the number of vehicles within the network. The maximum allowed power will be between 33-44 dBm EIRP with an expected range of up to 1000

meters. The range for message transmission can be extended by multi-hop messaging.

c) *Relative position calculation*: The position relevant information sent by the target vehicle can then be used to calculate the position of the target vehicle relative to the ego vehicle. Basically there are three different types of relative positioning:

- **Absolute position based relative positioning** by differencing of two absolute positions. Target vehicle and ego vehicle have to agree on a common reference system, such as WGS-84. This method is influenced by the whole set of GNSS measurement errors described above.
- **Code based relative positioning** uses a *Time Difference of Arrival (TDoA)* method with several simultaneous measurements on code basis (see above). Ego vehicle and target vehicle have to use identical satellites at the same time. Depending on the algorithm the following errors can be eliminated:
 - Single differencing between receivers eliminates pseudorange errors emerging from satellite clock bias, satellite orbit dislocation and ionospheric and tropospheric refraction. The different types of errors have a high correlation when signals emitted from the same satellite at the same time have a similar propagation path which is valid within short distances between ego vehicle and target vehicle as it is considered in this paper.
 - Double differencing between satellites additionally eliminates errors emerging from receiver clock offsets.
- **Carrier based relative positioning** uses TDoA on a carrier basis. Besides single and double differencing, triple differencing between epochs has to be considered in order to quantify integer cycle ambiguity.

Depending on the type of algorithm used for cooperative relative positioning, different types of position relevant data has to be transmitted between the target vehicle and the ego vehicle. Whereas absolute position based relative positioning has lower accuracy but can be encoded in a few bytes (e.g. 2x2 Bytes (Latitude-Longitude) according to [13]), pseudorange based relative positioning has higher accuracy but requires about 10 times as much data to encode (e.g. 8x5 Bytes = 8 pseudorange measurements encoded in 5 Bytes). Carrier phase based relative positioning has a even higher accuracy but requires considerably longer messages. Evidently, for reaching higher accuracy longer messages have to be accepted. Thus for the final protocol specification a respective tradeoff between message length and position accuracy has to be defined.

III. HYBRID DETECTION AND RANGING

Goal of DaR methods that conform to requirements of a *Situation-aware Driver Assistance System* is to gain a reliable and accurate position estimation of all target vehicles within the relevant scope. A lot of work has already been done in fusing of different autonomous systems (e.g. Radar & Lidar) but all these systems mainly suffer from a common subset of error causes which have strong influence on reliability and accuracy. Examples as described in the previous section are the shadowing by obstacles (e.g. in road curvatures), sensitivity towards environmental influences (e.g. fog, rain, snow) and a narrow detection zone. On the other hand, cooperative DaR depends on the active participation of the target vehicle and therefore strongly depends on the penetration rate as well as the reliability and accuracy of self-positioning and the wireless transmission of position relevant information. The hybrid approach presented in this paper therefore combines autonomous and cooperative DaR methods

in a hybrid approach including an adaptive sensor fusion resulting in an increased reliability and accuracy which will be shown in the simulation results in section IV.

A. Reliable and accurate target tracking

Core component of our hybrid approach is the sensor fusion algorithm for the combination of autonomous and cooperative DaR. Independent of the type of sensor measurements are subject to incompleteness and inaccuracy. Therefore, the preferred fusion algorithm should filter the noisy sensor measurements $z_{1:k}$ over time $1 : k$ and adequately infer the state space x_k at time k which will include at least the relative position of the target vehicle. The prediction step of the dynamic state estimator is defined by:

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1} \quad (4)$$

The update step is defined by:

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})} \quad (5)$$

To solve the equations, we prefer particle filtering because it allows the usage of non-Gaussian measurement and movement noise and non-linear measurement and movement models [14], [15]. Especially for complex non-linear driver behavior modeling this is an essential requirement.

In cases where both measurements, i.e. measurements of autonomous and cooperative DaR can be used together, the reliability and accuracy can be increased significantly by the dynamic state estimation with independent measurement noises.

In the run-up to the fusion algorithm itself the independent measurements have to be transformed to a common local reference system. This reference system may for instance be a polar or a cartesian coordinate system which may be aligned to a fixed direction (e.g. geographical north pole), dynamically adjusted according to the ego heading or even road-aligned [16]

Originally measurements from autonomous systems are to a certain extent directional and the sensors have a fixed installation location and orientation. Thus the measurements are already aligned to the ego vehicle heading and position - possibly with a certain offset in orientation and location. Depending on the type and orientation of the local coordinate system, the measurements have to be transformed adequately.

Cooperative DaR systems are not inherently aligned to the ego vehicle heading. In cases where a heading aligned coordinate system is used the measurements have to be transformed adequately. Therefore the heading of the ego vehicle can be estimated by analyzing the steering angle. In order to determine the initial heading either further sensors, such as compass or gyroscope, are required or the initial heading has to be inferred by consecutive position measurements. For the translocation of the measurements the antenna positions of both vehicles have to be known. Whereas for the ego vehicle the antenna position can easily be determined, the antenna position of the target vehicle has to be standardized or has to be added to the position relevant information that is sent by the target vehicle. Furthermore the target vehicle size has to be annotated in order to allow the ego vehicle to reference the cooperative DaR measurement to the reflection point of the autonomous DaR independent of the target vehicle's heading.

B. System Architecture

The overall architecture of the *Situation-aware Driver Assistance System* using our hybrid approach for DaR is depicted in fig. 3.

Principally it uses autonomous and cooperative sensors as main input for the fusion algorithm. In order to predict future movement and align the reference system, further input, such as steering angle sensor and compass is used. The prediction is performed by a *State Model* including a realistic vehicle following model (e.g. Krauss model [17]). Sensor errors are represented by the *Sensor Model*. The results of the fusion, i.e. a reliable and accurate relative position of target vehicles, can then be used in the *Situation Analysis* to detect hazardous or inefficient situations. Last, this is used to adapt vehicle effectors, e.g. adjust the ACC controller or inform the driver by visual, verbal or tactile Human-Machine Interfaces.

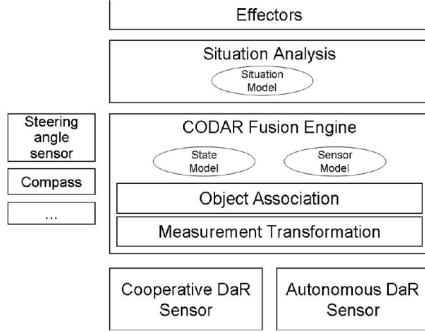


Fig. 3. CODAR Simulation Architecture

More information on the system architecture and the integration into the Situation-aware Driver Assistance System as a virtual sensor can be found in [18].

IV. PERFORMANCE EVALUATION

A. Simulation Environment

In order to validate our concepts we designed a simulation environment that allows the simulation of cooperative and autonomous DaR in realistic traffic environments. Within this paper we simulated a Long Range Radar sensor for the autonomous DaR with simulated measurement noise ($\sigma = 2m$) and the measurement errors described in section II. The cooperative DaR was based on absolute position based relative positioning with a constant Gaussian noise ($\sigma = 5m$). Transmission errors were not modeled adequately because a small number of vehicles and a high beaconing rate (10 Hz) of position relevant information was used and thus sporadic message losses can be neglected for the overall observation. An implementation of the CODAR fusion engine based on a particle filter with 1000 particles has been integrated into the simulation environment. 1000 particles turned out to have a sufficiently high accuracy/effectiveness and is computable under real-time conditions on a Intel Core 2 Duo (2.2 GHz) with 2GB RAM. For the initial implementation a simple random movement model and Gaussian 0-mean sensor models has been used.

B. Quantification Measures

For the quantification of DaR methods we propose two major measures:

a) *Detection Effectiveness*: The *Detection Effectiveness* is a measure to quantify the effectiveness of the DaR method. Rijsbergen defines effectiveness in terms of *Precision* and *Recall* [19].

Recall is a measure of completeness and specifies the probability that a real vehicle will be detected. It is defined by:

$$Recall \ R = \frac{TP}{TP + FN} \quad (6)$$

TP	True Positives \rightarrow Detected targets that correspond to real vehicles within the relevant scope
FN	False Negatives \rightarrow Undetected targets that correspond to real vehicles within the relevant scope

Precision is a measure of exactness and specifies the probability that a detected vehicle corresponds to a real vehicle. It is defined by:

$$Precision \ P = \frac{TP}{TP + FP} \quad (7)$$

TP	True Positives \rightarrow Detected targets that correspond to real vehicles within the relevant scope
FP	False Positives \rightarrow Detected targets that do not correspond to real vehicles, i.e. ghost targets, within the relevant scope

The scope in which the effectiveness is analyzed is determined by the application that requires the information. ACC, for instance, defines the scope as the headway of the ego vehicle up to a certain range that depends on the current speed, the following distance, etc.

b) *Position Error*: The second measure, the *Position Error*, is a measure for the accuracy of DaR methods. The *Position Error* is defined by the root mean square error whereas the error is the Euclidean distance between the estimated position and the real position of the target vehicle. It is defined by:

$$PE = \sqrt{E[\|\hat{X} - X\|_2]} \quad (8)$$

X	Real distance to the target vehicle
\hat{X}	Estimated distance to the target vehicle

C. Simulation Results

Figures 4-7 show the absolute number of vehicles (solid line), the number of detected vehicles by standalone Radar (dark grey) and the number of vehicles detected by our hybrid approach (light grey) in the form of stems at the bottom of each figure. The black stems illustrate false positives. The simulated test drive has a duration of 10s.

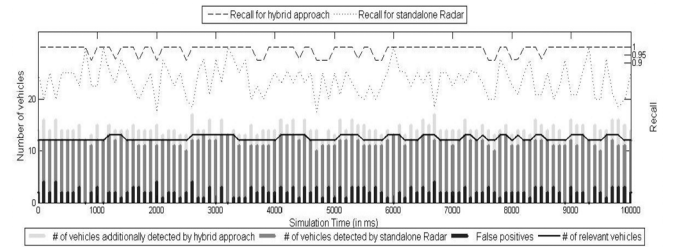


Fig. 4. Recall for ACC scope

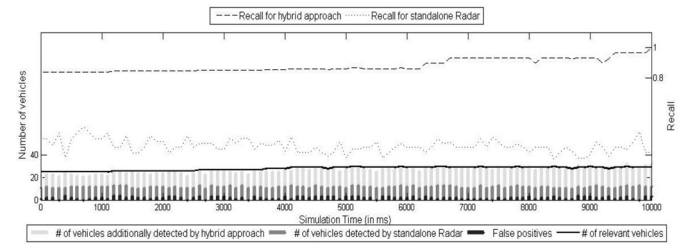


Fig. 5. Recall for full headway scope

The analyzed scenario is similar to the scenario shown in figure 1. The ego vehicle is driving on the left most lane of a three-lane road. Both other lanes are heavily occupied by vehicles with slower speed. The relevant scope of figure 4 and 6 is the scope defined by

the detection zone of a Radar system with 6° azimuth beamwidth and a range of 150 m. In figure 5 and 7 we used the same range as before, i.e. 150 m, but a larger angle of 180° . This scope will be in particular important for future safety applications that will take all vehicles within the ego headway into account in order to enable accurately timed situation-specific driver assistance.

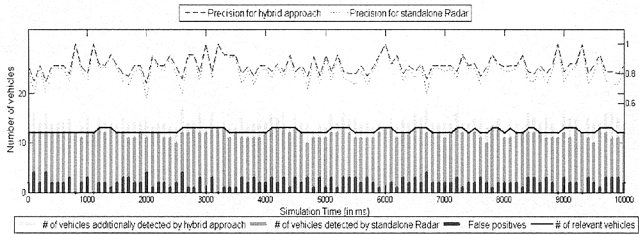


Fig. 6. Precision for ACC scope

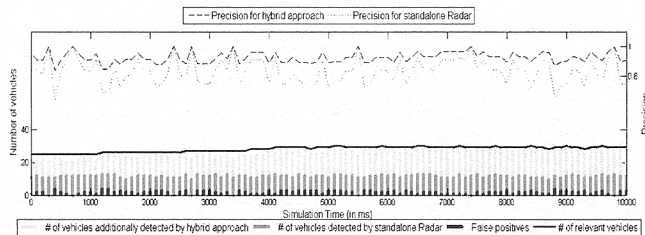


Fig. 7. Precision for full headway scope

Evidently, in figure 4 and 6 the number of vehicles detected by standalone Radar is nearly as high as the number of relevant vehicles because of the optimal case that the relevant scope and the scope of the detection sensor is identical. But it has to be recognized that this number is affected by undetected vehicles (FN) as well as wrongly detected vehicles (FP). The number of vehicles detected by the hybrid approach hence is composed of:

- # of relevant vehicles
- # of vehicles undetected by autonomous DaR
- + # of wrongly detected vehicles
- + # of vehicle additionally detected by cooperative DaR

For the cooperative detection we assumed a penetration rate of equipped vehicles of 80%. Thus, not every vehicle can be detected by cooperative DaR alone.

To get a more detailed explanation of the depicted simulation results, figures 4-7 also show the results broken down into *Recall* and *Precision*. The simulation clearly shows that the hybrid approach has a more complete effectiveness (*Recall*) and a higher exactness (*Precision*).

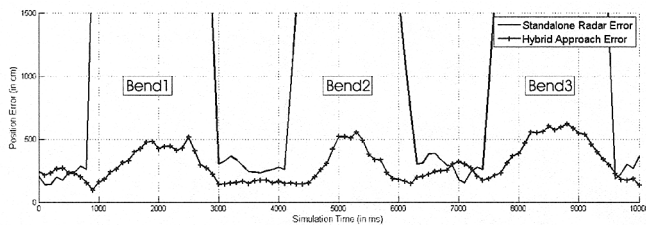


Fig. 8. Position Error

Figure 8 shows the *Position Error* of standalone Radar in contrast to the hybrid approach. The scenario we analyzed was a winding road (3 bends) with no other obstacles or disturbances but a single target vehicle within a constant distance to the ego vehicle. As can be seen in the figure autonomous DaR shows three measurement losses resulting in high errors when the target vehicle just drive round the curve and thus leaves the detection zone. During these periods the hybrid approach uses cooperative DaR standalone resulting in a higher *Position Error*. When the measurements from the autonomous DaR method get valid again the *Position Error* decreases. Although cooperative DaR has a considerably lower accuracy in our model the hybrid approach shows in almost every case an improvement of the *Position Error* in contrast to standalone Radar.

V. CONCLUSIONS

This paper identifies the main methods for Detection and Ranging of vehicles and their respective causes of error. In order to overcome these drawbacks a hybrid approach combining autonomous and cooperative DaR has been presented. The fusion of the independent measurements is based on a particle filter as a major part of the CODAR architecture. The simulation results showed that our concepts significantly increase the *Detection Effectiveness* quantified by *Recall* and *Precision* and decrease the *Position Error*.

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