A divergence mean-based geometric detector with a pre-processing procedure

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A B S T R A C T

This paper proposes a divergence mean-based geometric detector to deal with the problem of target detection in a clutter with the limited sample data. In particular, a covariance matrix is used to model the correlation of sample data in each cell in one coherent processing interval. This modeling method can avoid the poor Doppler resolution as well as the energy spread of the Doppler filter banks result from the fast Fourier transform. Moreover, a pre-processing procedure, conceived from the philosophy of the bilateral filtering in image denoising, is proposed and combined within the geometric detection framework. As the pre-processing procedure acts as the clutter suppression, the performance of geometric detector is improved. Numerical experiments and real clutter data are given to validate the effectiveness of our proposed method.

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1. Introduction

Improving the performance of target detection in a clutter is very important for a radar system. However, the classical fast Fourier transform (FFT) based constant false alarm rate (CFAR) detector [1] usually suffer from severe performance degradation with the limited sample data. This is because, the Doppler resolution is poor and the energy of the Doppler filter banks spreads, when the FFT is used to model the correlation of sample data. To address these problems, Barbaresco employed the structure of Riemannian manifold, and has proposed a generalized CFAR technique on a Riemannian manifold of Hermitian positive-definite (HPD) matrices. This method was named as the Riemannian mean-based geometric detector [2]. In this detector, the pulse data $z$ is modeled by a Gaussian random process with zero mean, and then the information of target is represented by an HPD matrix $R_i$. The detection statistic is defined as the distance between the HPD matrix $R_D$ of cell under test and the mean matrix $R$ calculated by the matrices of reference cells. The mean matrix denotes the clutter power level. Finally, the decision is made by comparing the statistic in each cell with an adaptive threshold $\gamma$. It can be referred to Fig. 1. As this detector takes the structure of HPD matrix space into account, it can be viewed as a geometric detector.

In this geometric detector, the sample data in each range cell in one CPI is modeled as an HPD matrix. The geometric metric is derived according to this parameterization [2,3]. On the basis of the metric, the existence and uniqueness of geometric mean had been proven in [4]. The geometric detector has been used to monitor the turbulence of a plane [5–7], target detection in coastal X-band and HF surface wave radars [2,3]. Many experimental results have shown that the performance of geometric detector outperforms the FFT-CFAR [3].

The Riemannian mean-based geometric detector and the classical FFT-CFAR detector are of similar schemes under the CFAR formulation. The main difference between the geometric detector and the FFT-CFAR detector in the following three aspects: 1) the model for the correlation of data is an HPD matrix, instead of the FFT coefficient; 2) the distance metric utilized is the geometric measure, and not the Euclidean distance; and 3) the average value of HPD matrices is the geometric mean, rather than the arithmetic average. These differences imply that the geometric detector performs on the HPD matrix space, in other words, the different geometry considered in detection. Furthermore, as the geometric detection method is performed on the HPD covariance matrix space, in this sense, the geometric method can be seemed as the
covariance matrix-based geometric detection. Under the generalized likelihood ratio test (GLRT), there are many covariance matrix-based algorithms, such as the Kelly's GLRT detector [8], the adaptive matched filter detector [9], and the normalized matched filter detector [10]. In particular, in [11–13], the authors exploit the priori information about the surrounding environment for estimating the covariance matrix to achieve a significant performance improvement. Another example is provided in [14], the Bayesian approach is employed to assume a suitable distribution about the unknown clutter covariance matrix, and similar methods also are found in [15]. The common goals of these detection algorithms are to attain a suitable covariance matrix in nonhomogeneous non-Gaussian clutter, and to improve the detection performance. The decisions about the presence and absence of a target with respect to these methods are made by Neyman-Pearson Lemma according to compare the value of test statistic with a threshold, which is set by fixing the false alarm probability at a certain level while maximizing the probability of detection. These covariance matrix–based algorithms do not consider the intrinsic structure embedding in covariance matrix space, and are based on the Neyman-Pearson criterion. Therefore, these methods are totally different from the geometric detection method which is based upon the properties of the Gaussian processes instead of the Neyman–Pearson Lemma.

Many metrics can be used to measure the closeness between any two points on the Riemannian manifold of HPD matrices. Different measurements can reflect different structures of this space. Many divergences can be used as measurements. Mentioned a few, the square loss is used to measure the distance between the two states in the regression; the Bhattacharyya divergence has employed to medical image segmentation [16,17]; and the Kullback-Leibler (KL) divergence has been widely used to measure the information difference between two probability distributions [18]. These metrics have achieved good results in many applications. In our previous work [19], we have studied a geometric detection method based on KL divergence. Experiments have shown that its performance outperforms the traditional FFT-CFAR detector.

In this paper, we explore the geometric detector base on different metrics. In particular, the Log-Euclidean distance [20], the Bhattacharyya divergence [21], and the Hellinger distance [22] are used as replacements of the Riemannian distance in the geometric detector. Based on the three metrics, the Log-Euclidean mean [23], the Bhattacharyya mean [16], and the Hellinger mean [22] of a finite set of HPD matrices are derived. As a result, a divergence mean-based geometric detector is developed. Moreover, we propose a weighted average filter which is combined within the geometric detector. This filter is conceived from the philosophy of the bilateral filtering in image denoising [24]. As this filter acts as a clutter suppression procedure, the detection performance can be improved.

The rest of this paper is organized as follows. In Section 2, we give a description about the signal model and signal manifold. In Section 3, the Riemannian geometry of space of HPD matrices and the divergence means are presented. The divergence mean-based geometric detector is developed in Section 4. Then, we evaluate the performances of the divergence mean-based geometric detector as well as the Riemannian mean-based geometric detector and the FFT-CFAR detector by simulated data and real clutter data in Section 5. Finally, conclusion is provided in Section 6.

1.1 Notation

Here are some notations for the descriptions of this article. A scalar x is denoted using the math italic. A matrix A and a vector x are noted as uppercase bold and lowercase bold, respectively. The conjugate transpose of matrix A is denoted as $A^\dagger$, tr(A) is the trace of matrix A. det(A) is the determinant of matrix A. I denotes the identity matrix. The set of all n-dimensional vectors is noted by $\mathbb{C}^n$. $H(n)$ is the set of all $n \times n$ Hermitian matrices. $|A|_p$ denotes the F-norm of matrix A. $P(n)$ is the space of all $n \times n$ HPD matrices. Finally, $\mathbb{E}(\cdot)$ denotes the statistical expectation.

2. Signal model and signal manifold

The radar usually sends several pulses to a moving target, and receives the return data which contains the phase information of this target. A certain model is used to capture the Doppler of target. In this paper, the Doppler is represented as the correlation of data $z = \{z_1, z_2, \ldots, z_n\}$, and is modeled as a multivariate Gaussian process with zero mean, $z \sim \mathcal{CN}(\mathbf{0}, \mathbf{R})$ [2].

$$p(z|\mathbf{R}) = \frac{1}{\pi^n |\mathbf{R}|} \exp\{-z^\dagger \mathbf{R}^{-1} z\} \quad (1)$$

here, the matrix $\mathbf{R}$ is an HPD matrix, and it can be computed as [2],

$$\mathbf{R} = \mathbb{E}[zz^\dagger] = \begin{bmatrix} r_0 & \bar{r}_1 & \ldots & \bar{r}_{n-1} \\ r_1 & r_0 & \ldots & \bar{r}_{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n-1} & \ldots & r_1 & r_0 \end{bmatrix} \quad (2)$$

$$r_k = \mathbb{E}[z_k z_{i+k}], \quad 0 \leq k \leq n-1, \quad 0 \leq i \leq n-1$$

where $r_k$ denotes the correlation coefficient of pulse data, and $\bar{r}_i$ is the complex conjugate of $r_i$. As there is not enough sample data to compute the statistical expectation $\mathbb{E}[z_k z_{i+k}]$, according to the ergodicity, it can be calculated by a finite time serial,

$$\hat{r}_k = \frac{1}{n-k} \sum_{i=0}^{n-1} z_j z_{j+k}, \quad 0 \leq k \leq n-1 \quad (3)$$

The pulse data $z = \{z_1, z_2, \ldots, z_n\}$ in each cell in one CPI is modeled by Eqs. (1) and (2), and represented by an HPD matrix $\mathbf{R}$. The pulse data $z$ is staying in the Euclidean space, and the HPD matrix $\mathbf{R}$ is viewed as a point in the manifold. Through this parameterization, the data $z$ is transformed into an $n$ dimensional non-liner manifold space,

$$\psi : C(n) \rightarrow \mathbb{P}(n), \quad z \rightarrow \mathbf{R} \in \mathbb{P}(n) \quad (4)$$

Here $\mathbb{P}(n)$ forms a differentiable Riemannian manifold [25] with non-positive curvature [26,27]. Through this modelling for the radar echo, the target detection should be performed in the manifold. In particular, the structure of matrix space can be considered. The manifold $\mathbb{P}(n)$ is a symmetric space [28], and more presentations can be found in [29].
3. Riemannian geometry of space of HPD matrices and divergence means

In this Section, we will introduce some basic mathematical knowledge on this manifold. For instance, the geometry of space of HPD matrices, divergence measures, and divergence means are presented.

3.1. The geometry of space of HPD matrices

Considering a set of matrices, all $n \times n$ Hermitian matrices constitute a space $\mathbb{H}(n) = \{ A \mid A^H = A \}$. For a Hermitian matrix $A$, it is a positive-definite matrix, if the quadratic form $x^H A x > 0$, $\forall x \in \mathbb{C}(n)$. All these HPD matrices are consisting of a convex symmetric cone \[ C^n \]

It is clear that $\mathbb{P}(n)$ is a non-linear space, and a point in this space is an HPD matrix. For any point $A$, its tangent space $\mathbb{T}_A$ is an $(n^2 - 1)$-dimensional space. The infinitesimal arclength at point $A$ can be given [30],

$$ds := \left( \text{tr} \left( A^{-1} dA \right) \right)^{1/2} = \| A^{-1/2} dA A^{-1/2} \|_F$$

This infinitesimal can define a metric on $\mathbb{P}(n)$. Then, $\mathbb{P}(n)$ can be called as a metric space. For any point $A$, the inner product can be defined as,

$$\langle R_1, R_2 \rangle_A = \text{tr} \left( A^{-1} R_1 A^{-1} R_2 \right), \quad \| R_1 \|_A = \langle R_1, R_1 \rangle_A^{1/2}$$

With the help of this metric, the distance between any two points $R_1, R_2$ on the space $\mathbb{P}(n)$ can be calculated as,

$$d^2_{R}(R_1, R_2) = \| \logm(R_1^{-1/2} R_2 R_1^{-1/2}) \|_F^2 = \sum_{k=1}^{n} \log^2(\lambda_k)$$

where $\lambda_k$ is the $k$th eigenvalue of $R_1^{-1/2} R_2 R_1^{-1/2}$, and $\logm(\cdot)$ is the logarithmic map on the manifold.

3.2. Divergence measures on the Riemannian manifold of HPD matrices

Many metrics can be used on the Riemannian manifold of HPD matrices. Different metrics have different properties, and reflect the different structure of manifold. In the following, the three geometric metrics are list in Table 1.

3.3. Divergence means for a finite set of HPD matrices

In general, for $m$ given positive real numbers $(x_1, x_2, ..., x_m)$, the arithmetic mean is computed as the sum of $m$ numbers divided by $m$. From a geometric viewpoint, the mean can be defined as,

$$x = \frac{1}{m} \sum_{i=1}^{m} x_i = \arg\min_{x>0} \sum_{i=1}^{m} |x - x_i|^2$$

Eq. (9) means that the mean is the minimum of the sum of the squared distances to the given point $x$. This definition can understand the arithmetic mean from a geometric essence.

### Table 1

<table>
<thead>
<tr>
<th>Divergence measures</th>
<th>Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-Euclidean [31]</td>
<td>$d_{LE}(R_1, R_2) = | \logm(R_1) - \logm(R_2) |_F$</td>
</tr>
<tr>
<td>Bhattacharyya [21]</td>
<td>$d_{B}(R_1, R_2) = 2 \sqrt{1 - \frac{1}{2} \sum_{i=1}^{m} \log \left( \frac{R_i}{R_{1i} R_{2i}} \right) \frac{1}{2} (R_i R_{1i} + R_i R_{2i})}$</td>
</tr>
<tr>
<td>Hellinger [22]</td>
<td>$d_{H}(R_1, R_2) = \sqrt{2 - 2 \left( R_1^{1/4} R_2^{1/4} / (R_1 + R_2)^{1/2} \right)^2}$</td>
</tr>
</tbody>
</table>

Similar to this geometric essence, for a set of HPD matrices $(R_1, R_2, ..., R_m)$, the Riemannian mean can be defined as,

$$\bar{R} = \arg\min_{R} \sum_{i=1}^{m} d^2_{R}(R, R_i)$$

where $d_{R}(\cdot, \cdot)$ represents the Riemannian distance. There is no analytical expression for Riemannian mean, and an iteration formula is given.

$$d_{R}(R_{t+1}, R_0) = \expm \left( -2 \varepsilon_t \sum_{k=1}^{m} \logm(R_{t+1}^{-1/2} R_{k} R_{t+1}^{-1/2}) \right) R_{t+1}^{1/2}$$

where $t$ is the index of iteration. $\varepsilon_t$ is the step size, and it varies with $t$ or constant. Similar to (15), a divergence mean for a set of HPD matrices $(R_1, R_2, ..., R_m)$ related to the divergence can be formulated,

$$\bar{R} = \arg\min_{R} \sum_{i=1}^{m} d^2_{R}(R, R_i)$$

where $d_{R}(\cdot, \cdot)$ denotes the divergence measure. The divergence means associated with the above three measures are listed in Table 2. Where $t$ denotes the index of iteration. The existence and uniqueness of these geometric means can be found in [31]. Their formulations can be computed using the fixed-point algorithm [32].

4. Divergence mean-based geometric detector with a weighted average filter

In this Section, we explore the geometric detector base on different divergence measures. Furthermore, we propose a weighted average filter which is conceived from the principle of the bilateral filtering in image denoising [24]. This filter, acts as the clutter suppression procedure, is combined within the framework of the geometric detector. In the following, we give a detail description about the geometric detector with a weight average filter.

### 4.1. Divergence mean-based geometric detector

In a practical environment of radar target detection, the signal to clutter ratio (SCR) of the matched filtered signal is still unsatisfactory, as the signal energy is submerged in the clutter. Then, a clutter suppression processing is extraordinarily necessary to improve the SCR. In this paper, the sample data is modeled as an
HPD matrix, and a clutter suppression algorithm needs to be designed on these HPD matrices. Particularly, the philosophy of bilateral filtering in image denoising [24] is employed for our filter. The principle of image denoising is that a noise-free pixel is estimated as a weighted average of image pixels, where each pixel is weighted according to its surrounding pixels in an image patch.

Based on this scheme, we propose a weighted averaging filter which is combined within our detector. As illustrated in Fig. 2, the correlation of pulse data \( z \) returned from a moving target in each cell is modelled as an HPD matrix \( \mathbf{R} \). All these HPD matrices constitute a Riemannian manifold. A weighted averaging filter is carried on according to the similarity of these matrices on manifold. Specially, each estimated matrix is replaced by a weighted average of its surrounding matrices. Based on these estimated matrices, the detection statistic is defined as the distance \( d(\mathbf{R}_d, \mathbf{R}) \) between the HPD matrix \( \mathbf{R}_d \) of cell under test and the mean matrix \( \mathbf{R} \) calculated by the matrices of reference cells. The mean matrix denotes the clutter power level. Finally, the decision is made by comparing the statistic in each cell with an adaptive threshold \( \gamma \). The rule of target detection can be formulated as follows,

\[
d(\mathbf{R}_d, \mathbf{R}) \begin{cases} \text{target present} &: \gamma, \\ \text{target absent} &: \gamma 
\end{cases}
\]

(13)

4.2. The weighted averaging filter on the Riemannian manifold

For an HPD matrix \( \mathbf{R} \) in the \( t \)th cell in one CPI, and its surrounding \( m \) matrices are given as \( \{ \mathbf{R}_1, \mathbf{R}_2, \ldots, \mathbf{R}_m \} \). A weighted strategy is employed, and the weighted matrix \( \mathbf{R}_{\text{wt}} \) can be estimated as follow,

\[
\mathbf{R}_{\text{wt}} = \frac{1}{m} \sum_{i=1}^{m} \mathbf{w}_i \mathbf{R}_i, \quad 0 \leq \mathbf{w}_i \leq 1, \quad \sum_{i=1}^{m} \mathbf{w}_i = 1
\]

(14)

where \( \mathbf{w}_i \) is the weight of \( i \)th HPD matrix. Similar to the bilateral filtering in image processing, the weight here is defined according the similarity between the matrix \( \mathbf{R} \) and a surrounding matrix \( \mathbf{R}_i \). In general, there are many ways to formulate the similarity between two elements. For instance, the reciprocal, the exponent, and the logarithm can be utilized into the definition. Here, we use the distance of between \( \mathbf{R} \) and \( \mathbf{R}_i \),

\[
\mathbf{w}_i = \frac{1}{W} \exp\{-d(\mathbf{R}, \mathbf{R}_i)/h^2\}
\]

(15)

where \( d(\mathbf{R}, \mathbf{R}_i) \) is the Riemannian distance. \( W = \sum_{i=1}^{m} \exp\{-d(\mathbf{R}, \mathbf{R}_i)/h^2\} \) is a normalizing factor, and \( h \) is a filtering parameter, which controls the exponential decay. \( m \) and \( h \) are two free parameters, and they are chosen according to the context.

5. Application of the target detection method

In this section, numerical experiments and real clutter data are performed to evaluate the detection performances of our proposed the three divergence means-based geometric detectors with the weighted averaging filter, namely the Log-Euclidean mean-based geometric detector (LogEMGD), the Bhattacharyya mean-based geometric detector (BhatMGD), and the Hellinger mean-based geometric detector (HeiMGD). The performances of these detectors are compared with the Riemannian mean-based geometric detector (RiemMGD) [2] and the classical FFT-CFAR detector [1].

5.1. Numerical experiments

The performances of: 1) the LogEMGD detector, the BhatMGD detector, and the HeiMGD detector, 2) the RiemMGD detector, (3) the FFT-CFAR detector are compared via Monte Carlo simulations. The data samples are from \( N = 7 \) received pulses. In our simulations, the radar received echo contains \( 7 \) pulses. The radar central frequency \( f_c \) is 9 GHz, and the pulse repetition frequency (PRF) is 1000 Hz. The target signal model is \( \mathbf{a} p, \) \( \mathbf{a} \) is a parameter accounting for the target backscattering and the channel propagation effects, and \( p \) is the target steering vector,

\[
p = \frac{1}{\sqrt{N}}|1, \exp(j2\pi f_c T), \ldots, \exp(j2\pi(N-1)f_c T)|^2
\]

(16)

where \( T \) is the pulse repetition interval, and \( f_c \) is the Doppler frequency. A target has an approximate constant velocity \( v = 5 \) m/s. As few pulses are considered, \( a \) is assumed to be constant. \( M = 16 \) range cells are considered as reference cells around cell under test, and used for averaging. In many high resolution radar scenarios, the Gaussian distribution assumption is not consistent with the actual situation, and cannot be used as clutter model. The compound Gaussian model is more suitable for describing non-Gaussian clutter. The compound Gaussian clutter can be written as the product of two independent random variables. The speckle component is a zero mean Gaussian process, and the texture component is a non-negative random process. It describes the average power level of clutter [33]. In our experiments, the non-Gaussian clutter is simulated via the K distribution, the probability density function of K distribution is given [34],

\[
p(x) = \frac{\sqrt{2v/\mu}}{2\pi \Gamma(\nu)} \left( \frac{\sqrt{2v/\mu}}{\nu} \right)^{\nu-1} K_{\nu-1} \left( \frac{\sqrt{2v/\mu}}{\nu} \right), \quad x \geq 0
\]

(17)

where \( \Gamma(\cdot) \) is the gamma function, and \( K_{\nu-1}(\cdot) \) is the modified Bessel function of the second kind with order \( \nu - 1 \). The shape parameter is \( \nu \), \( \mu \) denotes scale parameter.

A series of Monte Carlo simulation experiments are used to compare the performances between our proposed detector, the RiemMGD detector and the FFT-CFAR detector. The filter parameters of our proposed detector are \( m \) and \( h \), where \( m \) is the number of the range cells used for weighted filtering, and \( h \) denotes the filtering control parameter. \( m \) and \( h \) are free parameters. Different parameter values lead to different performances. In this simulation, we choose \( m = 11, h = 1; m = 11, h = 1.5 \); and \( m = 13, h = 1 \) respectively. These choices may not be the optimal. The purpose of selection of the parameter values is to enhance the target signal, and to reduce the clutter power simultaneously. Since there is not enough prior information, an analytical expression for the detection threshold cannot be obtained. In the experiment, the detection threshold is obtained by Monte Carlo experiments. Particularly, the detection statistic in the absence of the target is calculated by \( 10^6 \) experiments, and the threshold is determined according to a given false alarm probability \( (P_{fa}) \). To ensure the detection probability is
accurately estimated, we repeat 200 times simulations to estimate the detection probability under different SCRs. The detection probability is estimated by the relative frequencies. The $P_d$ vs SCRs under different $P_{fa}$ are given in Figs. 3–5. The SCR varies from $-10$ to $10$ dB, and the $P_{fa}$ are $10^{-3}$, $10^{-4}$ respectively. From Figs. 3–5 we can find that the performances of our proposed detector outperform the RiemMGD detector. Moreover, the detection performances of these geometric detectors are better than that of the FFT-CFAR detector.

5.2. Real clutter data

The real clutter data used here is collected from the McMaster University IPX radar, which is measured on the shore of Lake Ontario, between Toronto and Niagara Falls, Grimsby, Canada, in winter 1998 [35]. We exploit the two files 19980204_220046_ANTSTEP.cdf (file 1), and 19980205_185111 (file 2) to test the detection performances of the LogEMGD detector, the BhatMGD detector, the HelMGD detector, the RGD detector, and the
FFT-CFAR detector. The target information in these two datasets is not yet available, then we add a synthetic target with the model \( p \) presented as above. The IPIX radar has polarimetric information; shown results correspond to horizontal polarization (HH) only. For the two complex datasets, the fast time or range dimension consists of 27 samples, and the range resolution is 3 m. The number of samples in the slow-time dimension, is 60,000 with a pulse repetition frequency of 1000 Hz. The central frequency is 9.39 GHz, and the velocity is approximate constant, \( v = 5 \text{ m/s} \).

We use the first 50,000 pulses to estimate the threshold according to \( P_{fa} \). To limit the computational burden, we set the nominal \( P_{fa} = 10^{-3} \). The HPD matrix in each range cell is square matrix of order 5. \( 10^4 \) Monte Carlo runs to calculate the test statistics in the absence of target. 16 reference cells are used for computing the mean matrix. We use the followed 1000 pulses to carry out the target detection in the presence of target, and 200 times experiments are repeated to estimate the detection probability with different SCRs. The detection probability is estimated by the relative frequencies. Here, the filter parameters of the proposed detectors are also \( m = 11, h = 1; m = 11, h = 1.5; m = 13, h = 1 \), respectively.

Figs. 6–8 show the detection probability versus SCR with \( P_{fa} = 10^{-3} \). The SCR varies 0–15 dB and –10 to 15 dB in real clutter environment.

![Fig. 6. \( P_d \) versus SCR in real clutter environment, the LogEMGD detector.](image1)

![Fig. 7. \( P_d \) versus SCR in real clutter environment, the BhatMGD detector.](image2)

![Fig. 8. \( P_d \) versus SCR in real clutter environment, the HelMGD detector.](image3)
environment with an interval of 1 dB. It is clear from Figs. 6–8 that the proposed detectors have the best detection performance, and all these geometric detectors have better detection performance than the FFT-CFAR detector in these real clutter environments.

6. Conclusion

In this paper, we have proposed a divergence mean-based geometric detector. In particular, we have employed the philosophy of bilateral filtering in image denoising, and have proposed a weighted averaging filter. The filtered matrix in each cell is a weighted average of covariance matrices of its surrounding cells. It acts as a clutter suppression procedure, and can improve the detection performance. At the analysis stage, we have assessed the detection performance by giving plots of $P_d$ vs SCR in simulated experiments and real sea clutter. These results have shown that our proposed geometric detectors have better performance than the Riemannian mean-based geometric detector and the FFT-CFAR detector.

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