Dynamic Beam Tracking for Mobile Users

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Abstract. In wireless network planning, large-scale MIMO can be applied to beam forming technology, which can ensure the continuous signal of user receiver without interruption. When the user moves, beamforming technology requires beamswitching to reposition the user, which increases unnecessary overhead. In this paper, the user azimuth beam tracking algorithm based on Kalman filtering decomposed the user's trajectory in the actual scene, and used Kalman filtering algorithm to track the decomposed user's trajectory, so that the beam can be adjusted to point to the user in real time. Through experimental verification, Kalman filtering is relatively accurate in predicting the position of mobile users relative to the Angle information of base station, and the predicted beam can ensure the stability of users' connection, and at the same time achieve the purpose of reducing the number of beam-to-beam switching, reducing the overhead, improving the beam tracking efficiency, and making the connection more stable.

Keywords: 5G; large-scale MIMO; Beam forming; Beam tracking; Kalman filter.

1. Introduction

Large-scale MIMO uses larger-scale antennas at base stations and terminal sides. At present, 5G mainly adopts 64×64 MIMO. Large-scale MIMO technology can make the beam point to a specific direction by adjusting the parameters such as the number, amplitude and phase of the antenna array, so that the energy emitted by the antenna will not diffuse in all directions, and the energy will be concentrated on the specified beam, which can cover a larger area and reduce the interference between beams. Beam forming direction is controlled by changing the parameters of the antenna array to adjust the beam pointing to the moving user accurately. In the case of obstacles, the beam can be transmitted from the base station to the client based on the reflection or refraction of the ray. To ensure continuous seamless coverage, multiple beams should be sent in as many directions as possible on the base station side. Beam management technology can manage multiple beams sent by base stations. In the process of beam management, it is necessary to scan the beam in all directions. When the user's position moves, it is necessary to re-scan the beam to reposition the user's position. When the user's position moves for a long time, the re-scan method will cause a lot of overhead for scanning. Beam tracking technology can effectively reduce the switching times between beams, reduce the cost, predict the user's trajectory by using the user's historical location data, and ensure the stability of the connection between base station and user terminal.

Kalman filtering method is a time domain method. It integrates the theory of state space in the process of random estimation, and regards the whole process of signal processing as the output of a linear
system with Gaussian white noise. The state of input and output can be expressed by the equation of state. In the whole process, statistical properties are obtained by means of state equation and observation equation. Kalman filtering can not only be applied to complex dynamic systems, but also be used to predict the future trend of dynamic systems.

In this paper, we design a set of scheme aiming at the user's moving situation, using the azimuth-only Kalman filter algorithm to predict the user's trajectory according to the user's historical position data, and realize the purpose of dynamic tracking the user's moving position by beam. In this paper, the user position and the Angle change of the user position relative to the base station position, the real state and the predicted state of the user fit, and with the predicted state and the real state of the field intensity value as the evaluation index, to evaluate the whole scheme.

2. Related Work

At present, scholars at home and abroad have made many research achievements on the application of large-scale MIMO in beam forming. In literature [1], the author proposes a smart antenna based on Direction Of Arrival(DoA) based on the Global System for Mobile Communications (GSM) platform. In literature [2], the author introduces DoA estimation and proposes a multi-user beam tracking system, including array front end, beam tracker and Software Defined Radio (SDR). In literature [3], the author proposes a combined Minimum Mean Square Error (MMSE) robust beamforming and extended Kalman filter (EKF) tracking strategy to minimize beamforming Angle adaptation between mobile devices and fixed infrastructure in millimeter-wave environments. In literature [4,5], the author proposes a beam generated by recursive method. Channel tracking (RBCT) algorithm is used to speed up the beam tracking position, improve the tracking accuracy of the beam, and reduce the tracking cost. In literature [6], the author proposes a recursively generated beam tracking algorithm based on angular velocity for single-path beam tracking. Then, based on single-path beam tracking algorithm and RBCT algorithm, the author proposes a recursively generated beam tracking algorithm in two-path case. In literature [7], the author proposes a probability strategy, which can realize beam tracking with node mobility in the absence of dedicated synchronization signals. In literature [8], the author proposes a beam tracking algorithm based on reconstructed links for mobile scenes. This algorithm takes the data contained in the previous traffic as input and conducts beam tracking on the user's position, which can reduce the switching cost between beams. In literature [9], the author proposes a method for identifying errors caused by user terminal (UE) mobility, but does not propose any beam tracking algorithm to prevent such errors. In the literature [10], the author of base station (gNB) for fixed and mobile UE of end-to-end communication problems in a row, in the traditional extension on the multiple signal classification (MUSIC) algorithm, the introduction of effective direction of arrival (DOA) estimation algorithm, is put forward waiting for the position of the user and the user's location tracking algorithm, through the reference signal received power connection stability (RSRP) value judgment, the process can minimize switching times and costs, to ensure the stability of the base station and user signal connection; In the literature [11], the author for mobility higher position or uncertain, change a lot of users (such as unmanned aerial vehicles (uavs), etc.), this paper proposes a joint adaptive beam frequency allocation algorithm, as required by the quality of service (QoS) provides the optimization of the beam width of choice, in the user's location uncertain proportional fairness to maximize system.

3. System Model

3.1. System Principle

If the base station's antenna were to be beamed in all directions, the phone would receive only a limited amount of signal, and much of the energy would be wasted. If the signal can be focused into several beams through beam-forming and beamed specifically at each phone, the electromagnetic energy carrying the signal can travel further and the signal received by the phone will be stronger, as shown in figure 1.
Beam forming can be achieved by adjusting the amplitude and phase of signals transmitted by different antenna elements, even if the signals travel in different paths, as long as the phase is the same when they arrive at the phone, the effect of signal superposition enhancement can be achieved. See figure 2.

If each element in the array has the same type and orientation and is arranged on a straight line at equal intervals \( d \). Moreover, the current amplitude of each element antenna is \( I \), and the phase lags the same value \( \alpha \) in turn. Therefore, this antenna array is called uniform linear antenna array. The maximum radiation direction of the antenna array points to the direction of the array line, that is, the direction of \( \theta = 0 \). Such a linear array is called the end-shot linear array, and the normalized array factor of the common end-shot antenna array is

\[
F_n(\theta, \phi) = \sin \left[ \frac{nkd}{2} \left( \cos \theta - 1 \right) \right] \left( \sin \left[ \frac{kd}{2} \left( \cos \theta - 1 \right) \right] \right)^{-1}
\]

(1)

Where \( F_n(\theta, \phi) \) is a normalized factor, \( n \) is a matrix number, and the wave number \( k = \frac{2\pi}{\lambda} \).

\( d < \frac{\lambda}{2} \left( 1 - \frac{1}{2n} \right) \) is the condition for the normal terminal array direction diagram not to generate a cascade.

In order to improve the directivity of common terminal arrays, the current phase difference between control units can be used. In other words, the initial difference between adjacent elements is added to the phase delay of \( \frac{\pi}{n} \) on the basis of the ordinary terminal arrays. This uniform linear array is called the strongly directional terminal arrays. The normalization factor of the strongly directional terminal arrays is

\[
F'_n(\theta, \phi) = \sin \left( \frac{\pi}{2} \right) \sin \left( \frac{n}{2} \left[ kd \left( \cos \theta - 1 \right) - \frac{\pi}{n} \right] \right) \left( \sin \left( \frac{1}{2} \left[ kd \left( \cos \theta - 1 \right) - \frac{\pi}{n} \right] \right) \right)^{-1}
\]

(2)

According to the expression of normalization factor of strong directional end-emitter array, the beam forming diagram of 64×64 large-scale MIMO commonly used in 5G is obtained.

Assume that the user can through the SSB is connected to the base station, in the TDD system, base station and users to establish the initial connection is divided into three stages: the first stage is the base station side Tx beam and UE side beam scanning with Rx beam respectively, the second phase is
UE side Rx beam is changeless, Tx base station side beam scanning, the third stage is the base station Tx side beam is changeless, UE side Rx beam scanning, as shown in figure 3.

**Figure 3.** Initializes the connection establishment process

During positioning tracking, linear Kalman filter can obtain the estimated value of the target (the observed position) according to certain positioning techniques (such as Time of Arrival(ToA) positioning), and can also predict the current position (the predicted position) according to the motion model based on the experience of the position and velocity at the previous moment. The predicted and observed positions are weighted as the final positioning result, and the weight is determined by the degree of uncertainty of the predicted and observed positions. The state equation and the observation equation are

$$X(k+1) = \Phi X(k) + \Gamma W(k)$$  \hspace{1cm} (3)

$$Y(k) = HX(k) + V(k)$$  \hspace{1cm} (4)

Where $k$ stands for discrete time, $Y(k) \in \mathbb{R}^n$ stands for observation signal, $W(k) \in \mathbb{R}^m$ stands for the input white noise, $V(k) \in \mathbb{R}^m$ stands for the observation noise, $\Phi$ stands for the state transition matrix, $\Gamma$ stands for noise to drive the matrix, $H$ stands for observation matrix. Assuming that $W(k)$ and $V(k)$ are independent white noise with mean zero and variance matrices $Q$ and $R$ respectively, and the initial state $X(0) = \mu_0$, $E[(X(0) - \mu_0)(X(0) - \mu_0)^T] = P_0$, the recursive equations of Kalman filtering are

$$\hat{X}(k+1|k) = \Phi \hat{X}(k|k)$$  \hspace{1cm} (5)

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)\varepsilon(k+1)$$  \hspace{1cm} (6)

Where $\varepsilon(k+1) = Y(k+1) - H\hat{X}(k+1|k)$.

$$K(k+1) = P(k+1|k)H^T[H^T P(k+1|k) H + R]^{-1}$$  \hspace{1cm} (7)

$$P(k+1|k) = \Phi P(k|k) \Phi^T + \Gamma Q \Gamma^T$$  \hspace{1cm} (8)

$$P(k+1|k+1) = [I_n - K(k+1)H]P(k+1|k)$$  \hspace{1cm} (9)

Where $\hat{X}(0|0) = \mu_0, P(0|0) = P_0$. 
The extended Kalman filtering is based on the linear Kalman filtering and the linearization technique is used to transform the nonlinear system filtering problem into an approximate linear filtering problem. The dynamic equations of the discrete nonlinear system are:

$$X(k+1) = f[k, X(k)] + G(k)W(k)$$  \hspace{1cm} (10)\\
$$Z(k) = h[k, X(k)] + V(k)$$  \hspace{1cm} (11)\\

It is assumed that there is no input of control quantity, the noise generated in the process is white noise with zero mean value and Gaussian distribution, and the driving matrix $G(k)$ of the noise can be predicted in advance, and the observed noise $V(k)$ is white noise with gaussian distribution with zero additive mean value. At the same time, it is assumed that there is no effect between the noise $W(k)$ generated during the process and the noise $V(k)$ sequence observed. The principle of extended Kalman filtering is to divide the whole nonlinear system into local linearization operations. The state equation and the observation equation are:

$$X(k+1) = \Phi(k+1|k)X(k) + G(k)W(k) + \phi(k)$$  \hspace{1cm} (12)\\

Where, the initial value $X(0)$, $\phi(k)$ is a nonrandom external action.

$$Z(k) = H(k)X(k) + y(k) + V(k)$$  \hspace{1cm} (13)\\

Applying the basic equations of Kalman filtering, the recursive equation of extended Kalman filtering is:

$$X(k|k+1) = f(\hat{X}(k|k))$$  \hspace{1cm} (14)\\

$$P(k+1|k) = \Phi(k+1|k)P(k|k)\Phi^T(k+1|k) + Q(k+1)$$  \hspace{1cm} (15)\\

$$K(k+1) = P(k+1|k)H^T(k+1)[H(k+1)P(k+1|k)H^T(k+1) + R(k+1)]^{-1}$$  \hspace{1cm} (16)\\

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)[Z(k+1) - h(\hat{X}(k+1|k))]$$  \hspace{1cm} (17)\\

$$P(k+1) = [I - K(k+1)H(k+1)]P(k+1|k)$$  \hspace{1cm} (18)\\

Where, the filtering disposal is $X(0) = E[X(0)]$, and the initial value of the filtering error variance matrix is $P(0) = \text{var}[X(0)]$. The specific calculation process is as follows:

Step 1: Determine the initial state information $X(0)$, $Y(0)$ and the covariance matrix $P(0)$.

Step 2: Predict the state $X(k|k-1)$ of the next moment based on the state at the previous moment.

Step 3: Predict the observed value $Y(k|k-1)$ at the next moment based on the observed value at the previous moment.
Step 4: Take the derivative of the equation of state and get the state transition matrix $\Phi(k)$.

Step 5: Take the derivative of the observation equation and get the observation matrix $H(k)$.

Step 6: Obtain the covariance matrix to predict $P(k | k-1)$.

Step 7: Obtain Kalman filter gain $K(k)$.

Step 8: Update status $X(k)$.

Step 9: Update the covariance $P(k)$.

3.2. System Implementation

In this paper, user data simulation is carried out according to the real scenario in wireless network planning. According to the user’s initial position, locate the user, establish the initial connection between the base station and the user, predict the user’s position according to the change of the user’s position, and conduct beam tracking.

In the actual wireless network planning scenario, the user location will constantly change according to different street layouts, as shown in figure 4. The change of the user’s position in different scenarios will inevitably change the user’s Angle relative to the base station, so the azimuth-only target tracking algorithm based on extended Kalman filter can be adopted.

Figure 4. User position movement

According to the pedestrian's trajectory, the user's trajectory can be divided into segments of straight trajectory for trajectory prediction. Assuming the base station knows the user's initial location, the file can be read in during the simulation. The fitting diagram of the predicted trajectory of the extended Kalman filter and the user's real trajectory is shown in figure 5.

Figure 5. Azimuth-only target tracking trajectory based on extended Kalman Filter
It can be seen from figure 5 that there are some deviations between the predicted trajectory and the real trajectory, and the magnitude of the deviation is shown in figure 6, and the tracking error can be measured by the root mean square (RMS) error is

$$\text{RMS} = \frac{1}{n} \left( \sum_{i=1}^{n} (x'(i) - x(i))^2 + (y'(i) - y(i))^2 \right)^{1/2}$$

The conclusion can be drawn from figure 6 that the EKF algorithm has a general effect on the estimation of user position, because the state is four-dimensional information, while the observation information is only one-dimensional. Therefore, the observation Angle of the user can be used to fit the true Angle of the user relative to the base station, as shown in figure 7.

![Figure 6. Extended Kalman filter tracking error](image1)

![Figure 7. The observed Angle and the true Angle](image2)

From figure 7, we can see that there is little angle error between the user's real Angle and the observation Angle relative to the base station, so the observation Angle can be considered as the user's real Angle, and the beam is tracked and predicted, as shown in figure 8.

![Figure 8. Beam tracking diagram](image3)

![Figure 9. Beam direction error](image4)

In this paper, the ratio of the field intensity of the user's real position on the tracking beam to the field intensity of the predicted position on the tracking beam is converted into DB value to analyze the intensity of the user's received signal, as shown in figure 9.

4. Conclusion
Aiming at the problem of mobile user beam dynamic tracking, this paper presents a feasible and complete solution in wireless network planning. The program first obtains the user's initial position, in the wireless network planning software, can be in the form of documents for the import, the base station and the user side of beam scanning, set up the initial connection, using pure orientation based on extended Kalman filter algorithm of target tracking problem of different scenarios of user mobility...
can beam tracking, constantly updated user changes the point of view of adaptation of the beam. After system simulation, the beam direction error of the scheme is not different, which indicates that the scheme is feasible in wireless network planning software.

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