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A New Velocity Estimation Scheme based on Spatial Correlation of Wireless Communication Channel

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***Abstract*— We propose a new velocity estimation scheme for cellular communication systems that utilizes the azimuth spread (AS), delay spread (DS) and shadow fading of a mobile station (MS). Since the AS, DS and shadow fading are spatially correlated, the variation of the AS, DS and shadow fading of an MS is related to the velocity of the MS. In our proposed scheme, we use the AS, DS and shadow fading of an MS to estimate the velocity of the MS. Through analysis and numerical results, we show that we can accurately estimate the velocity.**

I. Introduction

In mobile cellular communication systems, almost every MS moves with certain velocity, because an MS moves with a person who carries it. Given that the person may be riding a bus or walking in a park, the velocity of an MS varies a great deal. And the velocity of an MS can also change time to time.

The velocity of an MS has influence on wireless communication systems in many aspects. In particular, it has influence on the doppler spread of wireless communication channel [1] [2]. The relation between the doppler spread and the velocity of an MS can be written as follows:

$$w_D = \frac{2\pi \cdot v_{MS} \cdot f_c}{c} \tag{1}$$

where f_c is carrier frequency, v_{MS} is the velocity of an MS and c is the velocity of electromagnetic waves. Given that maximum doppler spread is proportional to the velocity of the MS, the velocity is inversely proportional to the correlation time of wireless channel [1]. So, if an MS moves fast, the wireless communication channel also changes fast, which results in the increase of CQI (Channel Quality Indicator) feedbacks and the decrease of the accuracy of channel estimation. Needless to say, the increase of maximum doppler spread has influence on inter-carrier interference (ICI) which is related to the guard band of wireless communication systems.

The information of the velocity of an MS can be used in many application services of wireless communication systems. This information can be used to determine the parameters for hand-off [2], and can be also used to determine whether an MS should be allocated to microcells or macrocells in overlaid cell architectures. The information of velocity also can be used in the determination of CQI feedback schemes [3].

There are a lot of previous works to estimate the velocity of an MS. The velocity can be estimated by using the level crossing rate or the autocovariance of the signal envelope [4]. The maximum doppler spread of wireless communication channel is widely used to determine the velocity of the MS, because it is directly related to the velocity of an MS as we can see from eq.(1) of reference [2]. For the estimation of velocity, the location information of an MS, which can be found by using a GPS or other scheme [5], can be used. But, location estimation schemes [5] are not accurate in general, and using the GPS would have huge additional overhead in view of the system.

In this paper, we propose a novel velocity estimation scheme for cellular communication systems that is using the AS, DS and shadow fading of an MS. Given that the AS, DS and shadow fading of wireless communication channel is spatially correlated, we can use these channel components to estimate the velocity of an MS. Since AS, DS, and shadow fading can be measured at a base station (BS) by using mandatory uplink transmissions [3], there will be no feedback overhead caused by measurements.

II. Components of Wireless Communication Channel

There are many components of wireless communication channel that are spatially correlated, such as AS, DS, and shadow fading [7]. Many previous studies focus on the spatial correlation characteristics of AS, DS, and shadow fading [6] [7]. From [7], we can find that the values of AS, DS, and shadow fading at two distinct points are correlated, and the degree of correlation is related to the distance between these two points. So, in our proposed scheme, we use the values of the AS, DS and shadow fading of an MS at different points to find the velocity.

Before explaining the spatial correlation of AS, DS and shadow fading, we will make brief description on AS, DS and shadow fading which can be written as follows [7]:

$$\begin{aligned} h_A &= 10 \cdot (\sigma_A X + \mu_A) \\ h_D &= 10 \cdot (\sigma_D Y + \mu_D) \\ h_S &= \sigma_S Z \end{aligned} \tag{2}$$

where σ_A, σ_D, and σ_S denote the standard deviation of the AS, DS, and shadow fading, respectively, and h_A, h_D, and h_S denote the values of the AS, DS, and shadow fading in dBs, respectively. Also, μ_A and μ_D denote the mean of the AS and DS, respectively, and X, Y and Z represent Gaussian random variables with zero mean and unit variance [7]. From eq.(2), we can see that the Gaussian random variables X, Y and Z can be obtained by using the division and subtraction of σ_A, σ_D, σ_S, μ_A and μ_D as follows:

$$\begin{aligned} X &= \frac{1}{\sigma_A} \cdot (\frac{h_A}{10} - \mu_A) \\ Y &= \frac{1}{\sigma_D} \cdot (\frac{h_D}{10} - \mu_D) \\ Z &= \frac{h_S}{\sigma_S} \end{aligned} \tag{3}$$

Let $\rho_{cor}(d)$ be the correlation of X, Y or Z at two points which are separated by distance d. Then, given that X, Y, and Z which are shown above, are spatially correlated, $\rho_{cor}(d)$ can be expressed as follows:

$$\rho_{cor}(d) = \exp(-\frac{d}{D_{ref}}) \tag{4}$$

where D_{ref} denotes the reference distance, whose value depends on the environment and is almost the same for AS, DS, and shadow fading. The value of D_{ref} can be found in [7] as shown in Table I.

TABLE I

TYPICAL VALUES OF D_{ref}

Environment	Value of D_{ref}
Typical Urban-32	45m
Typical Urban-20	55m
Bad Urban	120m

The AS, DS, and shadow fading of an MS are cross-correlated to each other. The value of cross correlation can be found in [7]. Let σ_{AS}, σ_{AD} and σ_{DS} denote the cross correlation between AS and shadow fading, the cross correlation between AS and DS, and the cross correlation between DS and shadow fading, respectively. And also let X', Y' and Z' be the independent Gaussian random variables with zero mean and unit variance. Then, X, Y and Z can be written as follows:

$$\begin{aligned} X &= X' \\ Y &= \sigma_{AD}X' + (1-\sigma_{AD})Y' \\ Z &= \sigma_{AS}X' + KY' + (1-\sigma_{AS}-K)Z' \end{aligned} \tag{5}$$

where $K = \frac{\sigma_{DS}-\sigma_{AD}\sigma_{AS}}{1-\sigma_{AD}}$. By using eq.(5), we can eliminate the cross correlation between X, Y and Z, and obtain independent Gaussian random variables. The elimination of the cross correlation is important to ease analysis, because when there is no cross correlation between X, Y and Z, we can treat them independently. If there exists a cross correlation, we should consider them altogether.

III. Proposed Scheme

In our proposed scheme, we assume that a BS can measure the AS, DS, and shadow fading of an MS by using an uplink transmission signal. Since an MS in a cellular system periodically transmits uplink signals, such as a ranging signal, to the BS [3], the MS does not need to transmit an additional signal to the BS for the measurement of the AS, DS, and shadow fading. Therefore, the proposed scheme will not cause large overhead. Only the computational complexity of the BS will increase a little due to the calculation of AS, DS, and shadow fading. In our proposed scheme, these measurements are used to find the velocity of an MS. In some cases, the BS may be unable to obtain all the values of AS, DS or shadow fading due to the lack of measurement capability. In this case, only one or two components can be used for our proposed scheme, and the other components can be thrown away. Then, the number of samples should be increased.

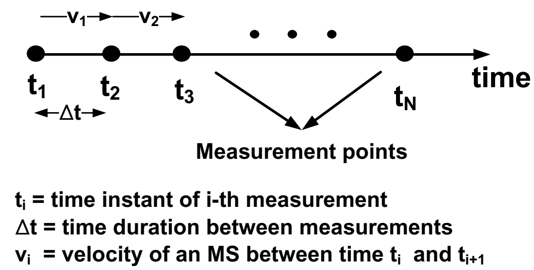

Fig. 1. Measurement of AS, DS and shadow fading

In our proposed scheme, a BS first periodically measures the AS, DS, and shadow fading of an MS. We denote the time interval between measurements as Δt and assume that the velocity of the MS can change only at each measurement point. The measurement scenario is depicted in Fig.1.

Then, by using eq.(3) and eq.(5), X', Y' and Z' can be expressed as following:

$$\begin{aligned} X' &= X \\ Y' &= \frac{1}{1-\sigma_{AD}}(Y - \sigma_{AD}X') \\ Z' &= \frac{1}{1-\sigma_{AS}-K}(Z - \sigma_{AS}X' - KY') \end{aligned} \tag{6}$$

Now, we calculate the difference in X', Y', and Z' between two measurement points. Let X_1', Y_1', and Z_1' be the values of X', Y', and Z' at one point and X_2', Y_2', and Z_2' be the values of X', Y', and Z' at an another point. Let X'', Y'', and Z'' be the difference between these two random variables, $(X_1' - X_2')$, $(Y_1' - Y_2')$, and $(Z_1' - Z_2')$, respectively. Then, the X', Y', and Z' of the two points are jointly Gaussian random variables and X'', Y'', and Z'' are the linear combinations of X', Y', and Z'. So, X'', Y'', and Z'' are also Gaussian random variables [8]. By using the spatial correlation of two points that are separated by distance d, the mean of X'' can be expressed as follows:

$$\mu_{X''} = E[X''] = E[X_1' - X_2'] = 0 - 0 = 0 \tag{7}$$

And, the variance of X'' can be described as following:

$$\begin{aligned} \sigma_{X''}^2 &= E[X''^2] = E[(X_1' - X_2')^2] \\ &= 2(\sigma_{X'}^2 - \rho_{cor}(d)) \\ &= 2(1 - \exp(-\frac{d}{D_{ref}})) \end{aligned} \tag{8}$$

where $\sigma^2_{X'}$ is the variance of X'. The mean and the variance of Y'' and Z'' can be derived similarly. We can obtain three independent random variables X'', Y'', and Z'' from a pair of points, and their variance is related to the distance between points.

We will use the variance of X'', Y'', and Z'' to find the velocity of an MS. In this paper, we assume that the BS measures the AS, DS and shadow fading at N points as shown in Fig.1, so the total time spent for the measurements is $(N-1)\cdot\Delta t$, because we assume that the interval between measurements is Δt. And by using these measurements, we can get $(N-1)$ samples. Then, we calculate the variance of X'', Y'', and Z''. Given that the variance of X'', Y'', and Z'' are the same, we use all the samples of X'', Y'', and Z'' together and get one variance value which is denoted as "σ^2_{ADS}". Theoretically, $\sigma^2_{ADS} = \sigma^2_{X''} = \sigma^2_{Y''} = \sigma^2_{Z''}$.

By using the σ^2_{ADS}, we can estimate the velocity of an MS because it is directly related to the distance between measurement points according to eq.(8). If the velocity of the MS does not change during the entire measurement, we can obtain the velocity of the MS by using eq.(8) as follows:

$$\begin{aligned} \sigma^2_{ADS} &= 2(1-\exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})) \\ \exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}}) &= 1-\tfrac{\sigma^2_{ADS}}{2} \\ v_{MS} &= -\tfrac{D_{ref}}{\Delta t}\log(1-\tfrac{\sigma^2_{ADS}}{2}) \end{aligned} \tag{9}$$

where v_{MS} is the velocity of the MS. By using eq.(9), we can calculate the velocity.

But the velocity of an MS can change during the measurement, because the duration of the measurement may be quite long. So, we should consider the variation of the velocity during the measurement. In this paper, we assume that when the velocity of an MS changes, the objective of velocity estimation is to find the average velocity of the MS, v_{MS_avg}. To see the effect of the variation of the velocity, we assume that an MS can change the velocity in every measurement points and assume that the velocity of the MS, v_{MS}, is random variable and its probability density function(pdf) is $f(v_{MS})$. Then, we need to find the mean of v_{MS}. First, we calculate the variance σ^2_{ADS} that will be observed as follows when the velocity of an MS is a random variable:

$$\begin{aligned} \sigma^2_{ADS} &= \mathrm{E}[\sigma^2_{v_{MS}}] \\ &= \mathrm{E}[2(1-\exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}}))] \\ &= 2-2\cdot\mathrm{E}[-\exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})] \\ &= 2-2\cdot\int_{-\infty}^{\infty}-\exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})\cdot f(v_{MS})\,dv_{MS} \\ &= 2-2\cdot F_L(\tfrac{\Delta t}{D_{ref}}) \end{aligned} \tag{10}$$

where $F_L(s)$ is the two-sided Laplace transform of $f(v_{MS})$. As we can see from the eq.(10), we cannot obtain v_{MS_avg} by using eq.(9,) because in general, $F_L(\frac{\Delta t}{D_{ref}}) \neq \exp(-\frac{\Delta t\cdot v_{MS\_avg}}{D_{ref}})$. The equality $F_L(\frac{\Delta t}{D_{ref}}) = \exp(-\frac{\Delta t\cdot v_{MS}}{D_{ref}})$ is only satisfied when $f(v_{MS}) = \delta(t-v_{MS\_avg})$, because the Laplace transform of shift function $\delta(t-\tau)$ is $\exp(-\tau s)$ [9]. It agrees with our intuitions because $f(v_{MS}) = \delta(t-v_{MS\_avg})$ means that the velocity of an MS is constant, which is the assumption of eq.(9).

If the distribution of the velocity of an MS is known, eq.(10) can be used to find the velocity. We calculate the σ^2_{ADS} when the velocity of an MS has a Gaussian distribution or an exponential distribution, based on the equation of σ^2_{ADS}, and we find optimal equation to estimate $v_{MS_{avg}}$.

i) In case that the velocity of an MS has a Gaussian distribution

If the distribution of v_{MS} is a Gaussian distribution, then $f(v_{MS}) = \frac{1}{\sqrt{2\pi}\sigma_{v_{MS}}}\exp(-\frac{(v_{MS}-v_{MS\_avg})^2}{2\sigma^2_{v_{MS}}})$, where $\sigma_{v_{MS}}$ is the variance of the velocity of an MS. If we know the value of $\sigma_{v_{MS}}$, we can easily calculate v_{MS_avg} by using σ^2_{ADS}. Given that the moment generating function (MGF) of gaussian distribution is $\exp(\mu t+\frac{\sigma^2 t^2}{2})$, σ_{ADS} can be calculated as follows by using eq.(10) [8]:

$$\begin{aligned} \sigma^2_{ADS} &= 2-2\cdot F_L(\tfrac{\Delta t}{D_{ref}}) \\ &= 2-2\cdot\exp(-v_{MS\_avg}\tfrac{\Delta t}{D_{ref}}+\tfrac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}) \end{aligned} \tag{11}$$

From eq.(11), we can obtain v_{MS_avg} by simple calculation as follows:

$$v_{MS\_avg} = \frac{(\sigma_{v_{MS}})^2\frac{\Delta t}{D_{ref}}}{2} - \frac{D_{ref}}{\Delta t}\log(\frac{2-\sigma^2_{ADS}}{2}) \tag{12}$$

But, given that we can not know the $\sigma_{v_{MS}}$ in general, we need a new estimation scheme that does not need $\sigma_{v_{MS}}$. To obtain this estimation, we simply assume that $|v_{MS\_avg}\frac{\Delta t}{D_{ref}}| \gg |\frac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}|$ and ignore $\frac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}$ term. Then, we can obtain approximated v_{MS_avg} by just removing $\sigma_{v_{MS}}$ from eq.(12) as follows:

$$v_{MS\_avg} = -\frac{D_{ref}}{\Delta t}\log(\frac{2-\sigma^2_{ADS}}{2}) \tag{13}$$

We can find that eq.(9) and eq.(13) are identical, because in the derivation of eq.(13), we assume that $\sigma_{v_{MS}} \approx 0$, which removes the statistical characteristics of the velocity of an MS.

ii) In case that the velocity of an MS has an exponential distribution

If the distribution of v_{MS} is an exponential distribution, $f(v_{MS}) = \frac{1}{v_{MS\_avg}}\exp(-\frac{v_{MS}}{v_{MS\_avg}})$. Given that the MGF of exponential distribution is $(1-\frac{t}{\lambda})^{-1}$ [8], σ_{ADS} can be calculated as follows by using eq.(10):

$$\begin{aligned} \sigma^2_{ADS} &= 2-2\cdot F_L(\tfrac{\Delta t}{D_{ref}}) \\ &= 2-2\frac{1}{\frac{\Delta t}{D_{ref}}\cdot v_{MS\_avg}+1} \end{aligned} \tag{14}$$

From eq.(14), we can obtain v_{MS_avg} by simple calculation as follows:

$$v_{MS\_avg} = \frac{D_{ref}}{\Delta t}\cdot\frac{\sigma^2_{ADS}}{2-\sigma^2_{ADS}} \tag{15}$$

But, in some cases, the distribution of the velocity of an MS may not be known. Then, we can not use eq.(10) to find v_{MS_avg}. Even if the velocity of the MS is known, the Laplace transform of the distribution of velocity cannot be found, or it is hard to find close form solution for v_{MS_avg}. So, we need some approximated estimation to deal with these situations.

We can approximate eq.(10) by using the Taylor series of $\exp(x)$. Given that x is small, $\exp(x)$ can be approximated to $1+x+\frac{x^2}{2!}+\cdots\frac{x^n}{n!}+\cdots$ by using Taylor series. Then, eq.(10) can be approximated as follows:

$$\begin{aligned}\sigma^2_{ADS} &= 2-2\cdot\int_{-\infty}^{\infty}-\exp(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})\cdot f(v_{MS})\ dv_{MS} \\ &= 2-2\cdot\int_{-\infty}^{\infty}(1-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}}+\tfrac{1}{2}\cdot(\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})^2\cdots \\ &\quad +\tfrac{1}{n!}\cdot(-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})^n\cdots)\times f(v_{MS})\ dv_{MS}\end{aligned} \tag{16}$$

If $\frac{\Delta t\cdot v_{MS}}{D_{ref}}\approx 0$, we can approximate eq.(16) further as follows:

$$\begin{aligned}\sigma^2_{ADS} &\approx 2-2\cdot\int_{-\infty}^{\infty}(1-\tfrac{\Delta t\cdot v_{MS}}{D_{ref}})\cdot f(v_{MS})\ dv_{MS} \\ &= 2-2(1-\tfrac{\Delta t\cdot v_{MS\_avg}}{D_{ref}})\end{aligned} \tag{17}$$

where we ignore the term $\frac{1}{2}\cdot(\frac{\Delta t\cdot v_{MS}}{D_{ref}})^2\cdots+\frac{1}{n!}\cdot(-\frac{\Delta t\cdot v_{MS}}{D_{ref}})^n\cdots$, because $\frac{\Delta t\cdot v_{MS}}{D_{ref}}\approx 0$.

Our assumption like $\frac{\Delta t\cdot v_{MS}}{D_{ref}}\approx 0$ is reasonable because in general, D_{ref} is larger than 50m as we can see from Table I, v_{MS} is less than 120km/h which corresponds to 33.3m/s and Δt should be less than 0.1s for an accurate velocity estimation. Then, $\frac{\Delta t\cdot v_{MS}}{D_{ref}}=0.066$, so it is valid to assume that $\frac{\Delta t\cdot v_{MS}}{D_{ref}}\approx 0$.

From eq.(18), we can obtain v_{MS_avg} by simple calculation as follows:

$$v_{MS\_avg} = \frac{D_{ref}\cdot\sigma^2_{ADS}}{2\Delta t} \tag{18}$$

As we can see from eq.(9), eq.(13), eq.(15) and eq.(18), when σ^2_{ADS} is small, all the velocity estimation schemes are the same. It means that when the observation period of AS, DS and shadow fading is small or the velocity of an MS is small, all the velocity estimation schemes will show similar performance.

IV. Performance Evaluation

In this section, we measure the performance of our proposed scheme. For performance evaluation, we assume that D_{ref} is 50m, which corresponds to the typical urban environment [7]. Also, we do not consider the measurement error of AS, DS and shadow fading. Moreover, we consider three velocity estimation schemes. First scheme is Constant Velocity Approximation based Estimation (CVAE) scheme based on eq.(9). Second scheme is based on eq.(18), which we call "Taylor Approximation based Estimation (TAE) scheme". Third scheme is based on eq.(12) or eq.(15) depending on $f(v_{MS})$, which we call "Exact Estimation (EE) scheme". These three estimation schemes have different characteristics. EE scheme shows the best performance, but it can only be used when the distribution of the velocity of an MS is known. CVAE scheme is derived on the assumption that the velocity of an MS is constant. TAE scheme is derived on the assumption that $\frac{\Delta t\cdot v_{MS}}{D_{ref}}\approx 0$.

First, we measure the performance of our propose scheme when the velocity of an MS is constant. We assume that

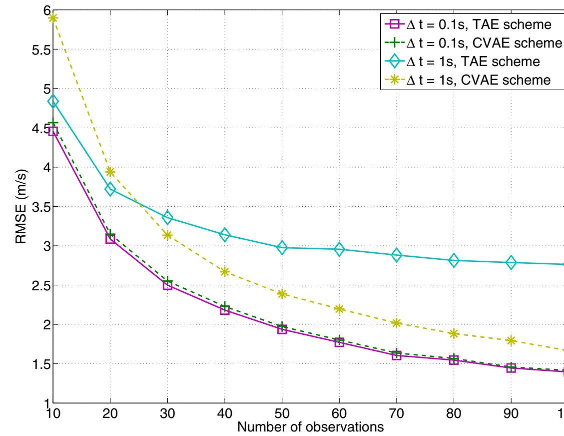

Fig. 2. RMSE of our proposed scheme with varying number of samples and Δt when the velocity of an MS is constant and 60km/h

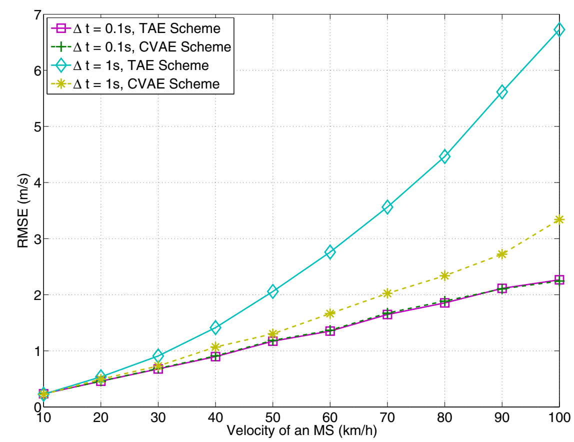

Fig. 3. RMSE of our proposed scheme with varying the velocity and Δt when the velocity of an MS is constant and the number of observations is 100

the velocity of the MS is 60km/h, and use two velocity estimation schemes which are CVAE scheme and TAE scheme. We do not consider EE scheme because it is identical to CVAE scheme when the velocity of an MS is constant. We measure the RMSE (Root Mean Square Error) of our proposed scheme when the number of observations and Δt change. We also investigate RMSE when the velocity changes. Numerical results are shown in Fig.2 and Fig.3.

As we can see from Fig.2, our proposed scheme shows better performance when the number of observations is large because as the number of observations increases, the measured variance will converge to $(1-\exp(-\frac{\Delta t\cdot v_{MS}}{D_{ref}}))$. At the convergence point, our CVAE scheme will find the exact velocity of an MS. When the number of observations increases, the RMSE of our proposed scheme converges to zero. From Fig.2, we can find that the RMSE of our proposed scheme increases as the velocity increases, which agrees with our intuitions.

We can also find from Fig.2 and Fig.3 that CVAE scheme and TAE scheme show similar performance when Δt is 0.1s, because when Δt is 0.1s, $\frac{\Delta t \cdot v_{MS}}{D_{ref}}$ is 0.033, which is close to zero. So, our assumption used in the derivation of eq.(9) is valid and these two schemes show similar performance. But when Δt is 1 sec, $\frac{\Delta t \cdot v_{MS}}{D_{ref}}$ becomes larger and the gap between the TAE scheme and the CVAE scheme increases. We can also see from Fig.3 that the gap between CVAE scheme and TAE scheme increases as the velocity of an MS increases because as the velocity increases, $\frac{\Delta t \cdot v_{MS}}{D_{ref}}$ increases, too.

From Fig.2, we can see that when the number of observations is small, the RMSE of TAE scheme is lower compared to that of CVAE scheme, which is contradictory to the discussion above. It is due to the estimation error of σ^2_{ADS}. In our proposed scheme, σ^2_{ADS} , which is essential to estimate the velocity of an MS, is measured from the observations. When the number of observation is not sufficient, the value of σ^2_{ADS} cannot be measured accurately and it may be different from the theoretical value which is $(1 - \exp(-\frac{\Delta t \cdot v_{MS}}{D_{ref}}))$. This measurement error causes the inaccuracy of velocity estimation. Eq.(18) is much more robust to error of σ^2_{ADS} compared to eq.(9), because eq.(18) is linear function and eq.(9) is log function. The first derivative of eq.(18) is smaller than that of eq.(9) when σ^2_{ADS} is smaller than 2, so the deviation from true velocity is small in eq.(18) compared to eq.(9), when σ^2_{ADS} is inaccurate. From this fact, we can find that the TAE scheme is more robust compared to the CVAE scheme. The TAE scheme has another advantages compared to the CVAE scheme. When the number of observation is small, σ^2_{ADS} can be larger than 2. Then, we cannot use CVAE based on eq.(9), because $1 - \frac{\sigma^2_{ADS}}{2} < 1$. However, we still can use TAE scheme based on eq.(18).

As we can see from Fig.2 and Fig.3, our proposed scheme is quite accurate. The RMSE of our proposed scheme when the velocity of an MS is 100km/h, is slightly larger than 2m/s. Our proposed scheme shows better performance, because when Δt is small, the accuracy of our proposed scheme increases and the time required for velocity estimation decreases. When Δt is 0.1, it takes 10 sec to acquire 100 observations. So, it is desirable to reduce the time interval between the observations as much as possible. But we cannot reduce Δt arbitrary, because it is related to the feasibility of the measurement of AS, DS and shadow fading.

Next, we measure the performance of our proposed scheme when the velocity of an MS is not constant. We assume that the distribution of the velocity of the MS is Gaussian distribution or exponential distribution. When the distribution of the velocity is a Gaussian distribution, we assume that the mean of the velocity is 100km/h and the variance is 200. When the distribution of the velocity is an exponential distribution, we assume that the mean of the velocity is 100km/h. We measure the RMSE of our proposed scheme when the number of observations and Δt change. Numerical results are shown in Fig.4 and Fig.5.

As we can see from Fig.4 and Fig.5, EE scheme shows lower RMSE compared to other schemes when the number of observations is large and $\Delta t = 1$ sec. When the number of observations is not sufficient, the RMSE of EE scheme shows the highest RMSE due to the incorrect estimation of σ^2_{ADS} as we discussed above. When $\Delta t = 0.1$s, the RMSE of all the three schemes shows similar performance because $\frac{\Delta t \cdot v_{MS}}{D_{ref}}$ is close to zero. But as the number of observations increases, the RMSE of EE scheme will converge to zero unlike other schemes, because we do not use approximation in the derivation of EE scheme. In Fig.5, when $\Delta t = 1$ sec, only the EE scheme converges to zero while TAE scheme converges to 10 m/s and CVAE scheme converges to 6 m/s, because in this case, our approximation causes large error.

We can also find from Fig.4 and Fig.5 that when the velocity of an MS changes, the performance of our proposed scheme becomes more poorer than the performance when the velocity does not change, because it takes more time to estimate the variance σ^2_{ADS}. From Fig.4, we can see that CVAE scheme

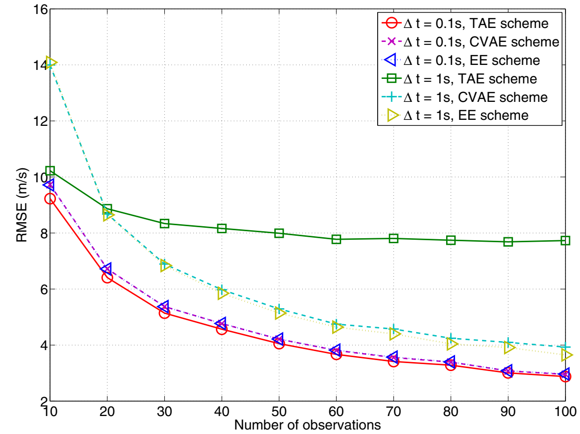

Fig. 4. RMSE of our proposed scheme with varying number of samples and Δt when the velocity of an MS has a Gaussian distribution

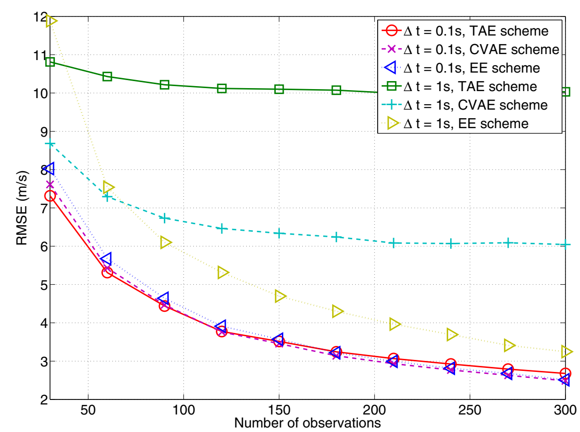

Fig. 5. RMSE of our proposed scheme with varying number of samples and Δt when the velocity of an MS has an exponential distribution

and EE scheme show similar performance when the pdf of velocity is Gaussian distribution and Δt = 1 sec, because in this case, $|v_{MS\_avg}\frac{\Delta t}{D_{ref}}|$ = 0.556 and $|\frac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}|$ = 0.04, and we can easily see that $|v_{MS\_avg}\frac{\Delta t}{D_{ref}}| \gg |\frac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}|$. As we have described in section III, when $|v_{MS\_avg}\frac{\Delta t}{D_{ref}}| \gg |\frac{(\sigma_{v_{MS}})^2(\frac{\Delta t}{D_{ref}})^2}{2}|$ and the velocity of an MS has a Gaussian distribution, CVAE scheme and EE scheme are identical. But as we can see from Fig.5, CVAE scheme and EE scheme do not show similar performance when the pdf of velocity is an exponential distribution, because such relation does not exist.

From Fig.4 and Fig.5, we can conclude that when the distribution of the velocity of an MS is not known, it is desirable to use TAE scheme when the number of observations is small or Δt is small. And it is desirable to use CVAE scheme when the number of observations is large.

V. Conclusions

We have proposed new velocity estimation schemes that use the spatial correlation of AS, DS, and shadow fading. In our proposed scheme, we use the values of AS, DS and shadow fading of an MS at different points to find the velocity of the MS, because they are directly related to the velocity of the MS. Through analysis and numerical results, we have shown that we can accurately find the velocity of an MS, especially when the time interval between observations is small. It has been shown that our proposed scheme performs better when the number of observation is large.

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