A New Velocity Estimator for Cellular Systems Based on Higher Order Crossings

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Abstract

Velocity estimation is of great importance in mobile cellular systems and is essential for satisfactory handoff performance, effective dynamic channel assignment, etc. In this contribution, the rate of maxima of the received signal envelope is proposed as a new velocity estimator. Required formulas are derived analytically, and the performance of this estimator in the presence of Gaussian noise, nonisotropic scattering, Rayleigh fading, and lognormal shadowing is compared with the conventional zero crossing rate estimator. This new estimator has much superior robustness against variations of SNR and scattering density, and similar to the zero crossing rate estimator, its quality deteriorates in the presence of shadowing.

1. Introduction

The statistics of flat fading-shadowing mobile channels in cellular systems are largely dependent on the Doppler frequency, f_m. The Doppler frequency is related to the velocity of mobile, ν, as $v = \lambda f_m$, where λ stands for the wavelength of the carrier. So efficient and on-line estimation of mobile velocity is of great importance in mobile communications, and ultimately provides good handoff performance and effective dynamic channel assignment [1].

In order to estimate the velocity of a mobile, the following quantities have already been used:

1- Zero crossing rate (ZCR) of the in-phase or quadrature component of the signal [2],
2- Level crossing rate (LCR) of signal envelope [2]- [6],
3- Autocovariance of the transformed envelope of the signal [7] [8],
4- Switching rate of diversity branches in a selection diversity combiner [9],
5- LCR of the signal envelope, combined with on-line change detection techniques [10].

In [1] [11], performance of the first three quantities, under different conditions, are studied extensively. It should be mentioned that in all of the above cases, magnitude of the velocity vector has been of concern. However, some authors have estimated the velocity vector instead [12].

ZCR and LCR based velocity estimators have proven to be efficient and also robust to variations of the propagation environment [1]. However, ZCR of the in-phase or quadrature component of the signal cannot be measured from the envelope. In fact, mean of the in-phase or quadrature component of the signal should be estimated and then subtracted from that component, and after that velocity can be estimated [1] (Note that in order to have the in-phase or quadrature component of the signal, we must have a coherent detector). On the other hand, LCR of the signal envelope can be obtained directly from the envelope. But for estimating the velocity, mean power of the signal must be estimated [1]. Due to the dependence of the mean power of the signal on the propagation loss, which depends on the distance between the mobile and base station as well as shadowing, this method is difficult to use [9]. Indeed, estimation of the mean power of the signal is a big problem in cellular systems and several issues should be taken into account in order to have a reliable estimate of the mean power of the signal [1].

In what follows, the rate of maxima (ROM) of the signal envelope is proposed as a new quantity for estimating the velocity of a mobile. In contrast to the previously mentioned ZCR and LCR based methods, in this method, velocity can be measured directly from the envelope (by counting the number of maxima, or equivalently, minima of the envelope), without any need for estimating the mean of the in-phase or quadrature component of the signal, or the mean power of the signal.

Generally speaking, LCR (with ZCR as a special case) of a random process is a first-order crossing measure, i.e. it depends only on the statistical properties of the random process and its first-order time derivative. On the other hand, higher-order crossing measures depend on the statistical properties of higher-order time derivatives of the random process. So, they potentially convey more information [13]. ROM of a random process is a second-order crossing measure, because it is equal to the number of negative-going zeros of the time derivative of that random process. Hence ROM may show better performance against noise, type of scattering, and fading-shadowing, in comparison to ZCR and LCR based methods.

2. Models of signal and noise

We assume that the received signal, $X(t)$, has the following form:

$$X(t) = I(t) + N(t)$$
$$= I_c(t)\cos(2\pi f_o t) - I_s(t)\sin(2\pi f_o t) + N(t)\,, \qquad (1)$$

where f_o is the carrier frequency, $I(t)$ is the resulting superposition of all multipath components at the output of the receiver antenna, $I_c(t)$ and $I_s(t)$ are the in-phase and quadrature components of $I(t)$ (two lowpass zero-mean Gaussian random processes), and $N(t)$ is the Gaussian noise with one-sided power spectral density η. Using the following representation for $N(t)$:

$$N(t) = N_c(t)\cos(2\pi f_o t) - N_s(t)\sin(2\pi f_o t)\,, \qquad (2)$$

with $N_c(t)$ and $N_s(t)$ as two lowpass zero-mean Gaussian random processes, $X(t)$ in (1) can be written as:

$$X(t) = \left[I_c(t) + N_c(t)\right]\cos(2\pi f_o t)$$
$$-\left[I_s(t) + N_s(t)\right]\sin(2\pi f_o t)\,. \qquad (3)$$

So $\Re(t)$, the envelope of $X(t)$ can be written as $\Re(t) = [X_c^2(t) + X_s^2(t)]^{1/2}$, where:

$$X_c(t) = I_c(t) + N_c(t), \quad X_s(t) = I_s(t) + N_s(t)\,. \qquad (4)$$

3. Power spectra and spectral moments of signal and noise

It is well known that the power spectrum of $I(t)$ can be written as [1]:

$$S_I(f) = \sigma^2\left[f_m^2 - (f - f_o)^2\right]^{-1/2}\left[G(\theta)p(\theta) + G(-\theta)p(-\theta)\right],$$
$$\left|f - f_o\right| \le f_m\,, \qquad (5)$$

where $S_I(f)$ is zero for $|f - f_o| > f_m$, σ^2 is the total power from all multipath components at the input of the receiver antenna, θ is the angle of the wave arrival, $G(.)$ is the receiver antenna gain pattern, and $p(.)$ is the scattering density, i.e. the density of the incident power on the receiver antenna. For a vertical monopole antenna: $G(\theta) = 3/2$. A useful model for $p(.)$ could be the von Mises density, widely used in the context of directional statistics [14]:

$$p(\theta) = [2\pi I_0(\kappa)]^{-1}\exp[\kappa\cos(\theta)],\ \ \kappa \ge 0,\ -\pi \le \theta < \pi\,, \qquad (6)$$

where $I_0(.)$ is the modified Bessel function of order zero, and parameter κ determines the directivity of the incoming waves. For $\kappa = 0$ we have isotropic scattering, i.e. $p(\theta) = 1/2\pi$; while for $\kappa > 0$ we get nonisotropic scattering. The polar plots of $p(\theta)$ versus θ, for different values of κ, are shown in Fig. 1. The von Mises density has three main advantages over the other scattering densities used for modeling nonisotropic scattering [15]: It results in closed form formulas for the spectral moments and correlation functions, includes both isotropic and nonisotropic scatterings as special cases, and its associated nonisotropic scattering is not necessarily unidirectional (as can be seen in Fig. 1).

The *n*th spectral moment of $I(t)$ is defined by:

$$b_n = (2\pi)^n \int_0^\infty (f - f_o)^n S_I(f)df, \quad n = 0, 1, 2, \ldots. \qquad (7)$$

For $G(\theta) = 3/2$ and $p(\theta)$ in (6), doing the integration in (7) results in:

$$b_n = b_0 (2\pi f_m)^n q_n(\kappa)\,, \qquad (8)$$

where $b_0 = 3\sigma^2/2$ is the power of $I(t)$, i.e.:

$$b_0 = \int_0^\infty S_I(f)df\,,$$

and:

$$q_0(\kappa) = 1,$$
$$q_1(\kappa) = I_1(\kappa)/I_0(\kappa),$$
$$q_2(\kappa) = \left[I_0(\kappa) + I_2(\kappa)\right]/2I_0(\kappa),$$
$$q_3(\kappa) = \left[3I_1(\kappa) + I_3(\kappa)\right]/4I_0(\kappa),$$
$$q_4(\kappa) = \left[3I_0(\kappa) + 4I_2(\kappa) + I_4(\kappa)\right]/8I_0(\kappa), \qquad (9)$$

with $I_n(.)$ as the modified Bessel function of order *n*.

Assuming that the bandwidth of the front-end filter in the receiver is maintained equal to $2f_m$ in an adaptive manner [1], the spectral moments of $N(t)$ are:

$$a_0 = 2f_m\eta,$$
$$a_1 = 0,$$
$$a_2 = a_0(2\pi f_m)^2/3,$$

$$a_3 = 0,$$
$$a_4 = a_0 (2\pi f_m)^4 / 5, \tag{10}$$
where a_0 is the noise power, i.e.:
$$a_0 = \int_0^{\infty} S_N(f) df \ .$$

Due to the independence of $I(t)$ and $N(t)$ in (1), $S_X(f) = S_I(f) + S_N(f)$. So for the spectral moments of $X(t)$ we have: $c_n = b_n + a_n$, and based on (8)-(10) we get:
$$c_0 = a_0(\gamma + 1),$$
$$c_1 = a_0 (2\pi f_m)\gamma\, q_1(\kappa),$$
$$c_2 = a_0 (2\pi f_m)^2 \left[\gamma\, q_2(\kappa) + 1/3\right],$$
$$c_3 = a_0 (2\pi f_m)^3 \gamma\, q_3(\kappa),$$
$$c_4 = a_0 (2\pi f_m)^4 \left[\gamma\, q_4(\kappa) + 1/5\right], \tag{11}$$
where $\gamma = b_0 / a_0$ is the signal-to-noise ratio (SNR). In the presence of lognormal shadowing, b_0, and consequently γ becomes a lognormal random variable.

4. The new velocity estimator

Here the goal is to estimate the velocity of mobile based on the received signal $X(t)$. Based on the characteristics of $I(t)$ and $N(t)$ in Section 3 and conditioned on γ, $\Re(t)$ is a Rayleigh random process, while $X_c(t)$ and $X_s(t)$ are Gaussian random processes. Now we introduce the new velocity estimator, together with the conventional estimator. Note that in what follows, the parameter κ is dropped to simplify the notation.

A. ROM of the envelope (new): According to [16] and conditioned on γ, ROM of $\Re(t)$ can be expressed as:
$$\mathrm{ROM}\left\{\Re(t) \middle| \gamma\right\} = \frac{1}{2\pi}\sqrt{\frac{c_0 c_4 + 3c_2^2 - 4c_1 c_3}{c_0 c_2 - c_1^2}} \ . \tag{12}$$
Based on (11) and after some simple algebric manipulations we get:
$$\mathrm{ROM}\left\{\Re(t) \middle| \gamma\right\} = f_m \times$$
$$\sqrt{\frac{(q_4 + 3q_2^2 - 4q_1 q_3)\gamma^2 + (q_4 + 2q_2 + 1/5)\gamma + 8/15}{(q_2 - q_1^2)\gamma^2 + (q_2 + 1/3)\gamma + 1/3}} \ . \tag{13}$$

B. ZCR of the in-phase or quadrature component (conventional): Based on [17] and conditioned on γ, ZCR of $X_s(t)$ (or equivalently, $X_c(t)$) is given by:
$$\mathrm{ZCR}\left\{X_s(t) \middle| \gamma\right\} = \frac{1}{2\pi}\sqrt{\frac{c_2}{c_0}} \ , \tag{14}$$
where upon application of (11) changes to:
$$\mathrm{ZCR}\left\{X_s(t) \middle| \gamma\right\} = f_m \sqrt{\frac{q_2\gamma + 1/3}{\gamma + 1}} \ . \tag{15}$$

5. Performance of the new velocity estimator

A. Gaussian noise and nonisotropic scattering: Conditioned on γ, $\rho(\kappa,\gamma) = \mathrm{ROM}\{\Re(t)|\gamma\} / f_m$ in (13) and $\zeta(\kappa,\gamma) = \mathrm{ZCR}\{X_s(t)|\gamma\} / f_m$ in (15) are plotted in Fig. 2 on the $\kappa - \gamma$ plane. According to this figure:
$$100 \times \left.\frac{\max(\rho) - \min(\rho)}{\max(\rho)}\right|_{0\le\kappa\le 30 \;\; 0\le\gamma\le 50} \approx 27\% \ ,$$
$$100 \times \left.\frac{\max(\zeta) - \min(\zeta)}{\max(\zeta)}\right|_{0\le\kappa\le 30 \;\; 0\le\gamma\le 50} \approx 41\% \ .$$
Therefore from this point of view ROM of $\Re(t)$ is less sensitive to the variations of κ and γ, hence superior to the ZCR of $X_s(t)$.

B. Gaussian noise, nonisotropic scattering, and lognormal shadowing: In this case γ has a lognormal density with parameters μ and σ. For $\mu = 7$, $\mathrm{ROM}\{\Re(t)\} / f_m$ and $\mathrm{ZCR}\{X_s(t)\} / f_m$ are plotted in Fig. 3 in the $\kappa - \gamma$ plane using numerical integration with respect to γ (for other values of μ we got similar behavior). According to this figure, shadowing has a disturbing effect on both ROM and ZCR, and it seems that there is no special preference in choosing either ROM or ZCR from this point of view.

6. Conclusion

In this paper, rate of maxima (ROM) of the received signal envelope was introduced as a new velocity estimator. Then its performance in the presence of noise, nonisotropic scattering, Rayleigh fading and lognormal shadowing was compared to a previously known velocity estimator, i.e. ZCR of the in-phase or quadrature component of the received signal. It was observed that ROM is more robust to changes is SNR and scattering density. Moreover, it was shown that in the presence of shadowing, performance of both estimators degrades significantly. The practical advantage of ROM is that it can be easily measured from the envelope, in contrast to ZCR that requires the coherent detector and then extraction of the mean value of the in-phase or quadrature component. Some practical issues regarding the measurement of ROM can be found in [18] [19].

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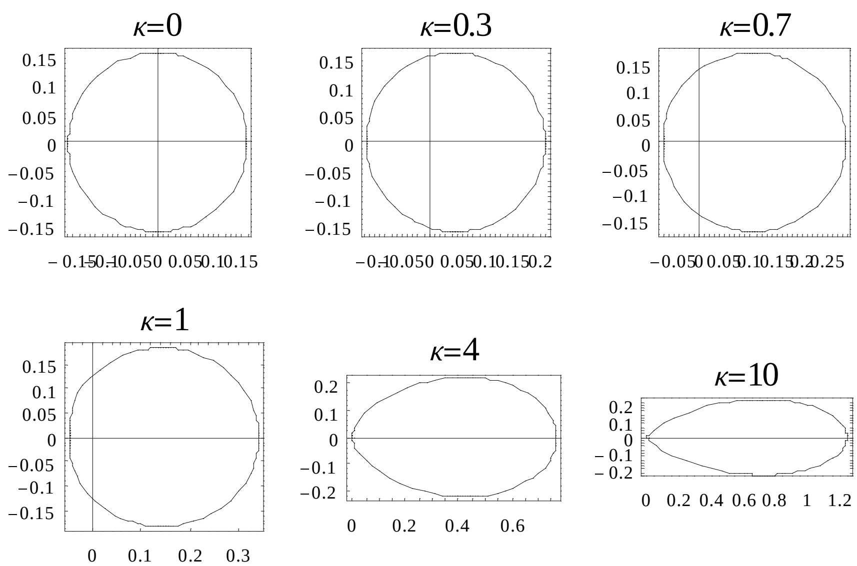

Figure 1. Polar plot of $p(\theta)$ **in terms of** θ **for** $\kappa = 0, 0.3, 0.7, 1, 4, 10$ **.**

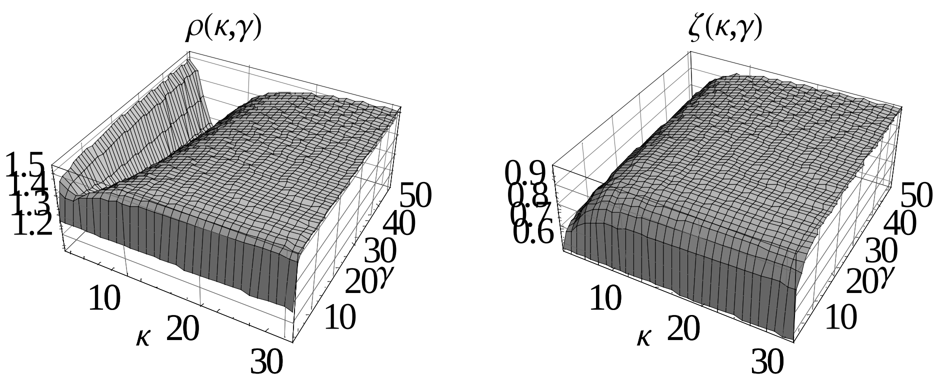

Figure 2. $\rho(\kappa,\gamma) = \mathrm{ROM}\{\Re(t)|\gamma\}/f_m$ **in (13) and** $\zeta(\kappa,\gamma) = \mathrm{ZCR}\{X_s(t)|\gamma\}/f_m$ **in (15).**

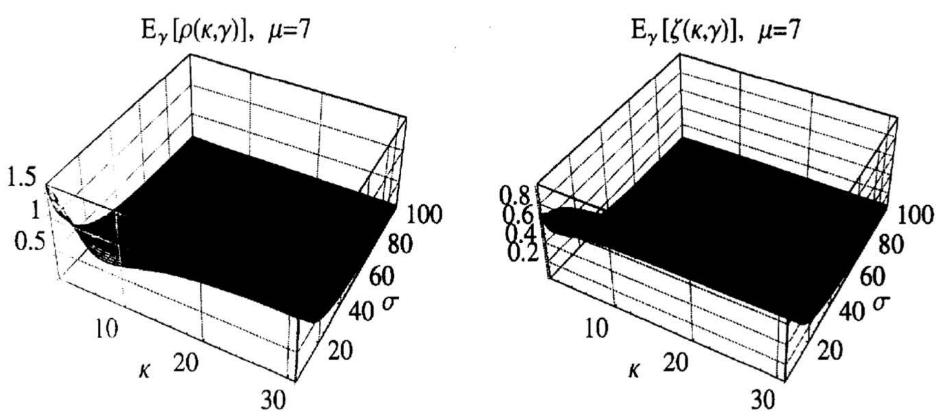

Fig. 3 $\mathrm{ROM}\{\Re(t)\}/f_m$ **and** $\mathrm{ZCR}\{X_s(t)\}/f_m$ **in the** $\kappa-\sigma$ **plane,** $\mu = 7$ **.**