

Cooperative Power Delay Profile Estimation for Vehicle-to-Infrastructure Communications

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ABSTRACT

Power adaptation is crucial to maximize the system capacity for orthogonal frequency multiple access (OFDM) systems, where power delay profile (PDP) should provide instantaneous signal power distribution. This paper proposes a cooperative PDP estimation method to mitigate the impact of imperfect CSI in vehicle-to-infrastructure (V2I) communication systems. To obtain accurate PDP, the movement characteristics of the vehicle including the location and velocity are well exploited, and PDP can be fitted from multiple vehicle observations. This paper mainly considers the impacts of different CSIs on path losses in the high-mobility scenario. Hence, we investigate a single/multiple user PDP estimation technique based on linear interpolation algorithm. Furthermore, we validate the proposed approach using traditional LMMSE channel estimation algorithm, and evaluate its performance in terms of channel estimation mean-square error (MSE) and bit error rate (BER). It is shown that the proposed algorithm can achieve results with low computational complexity and support reliable data transmission.

Keywords: Vehicle-to-Infrastructure communications, power delay profile estimation, imperfect channel state information, channel estimation, multi-user cooperation

1. INTRODUCTION

Adaptive modulation and coding can provide tremendous performance gains and high spectral efficiencies in OFDM systems. It requires that downlink channel state information (CSI), e.g., the power delay profile (PDP), the complex amplitude of each subcarrier or the noise variance, is generally available as a priori information at the transmitter. Among these, PDP is useful to depict the impacts of different CSIs in high-mobility scenario. However, the accurate CSI is difficult to obtain in practical system since the radio propagation is changing quickly in fast fading channels, resulting in imperfect or partial CSI. Especially, this situation will become particularly serious in high-mobility IEEE802.11p V2I communications for the CSI has been outdated, and the PDP estimates at current

location do not represent the real distribution of the received power over delays.

In time-varying fading channel, the estimated PDP can be converted from the channel impulse response (CIR). Thus, several familiar criterions, such as minimum mean square error (MMSE), maximum likelihood (ML), least squares (LS), have been well investigated for estimating the CIR [2-8]. By taking advantage of the cyclic prefix (CP) segment of OFDM symbols, many PDP estimators based on ML have been proposed [9], [10]. However, in all these works, perfect CSI is assumed and the issues of packet errors are ignored, and a considerable amount of research is for quasi-static, and revealed that the performance degradation is caused by both the correlation mismatch and the estimation error of delay parameters. Theoretically, the accurate PDP measurement at a fixed location can be approximated through the time averaged mean, nevertheless, this method is almost unavailable in high-mobility scenarios due to outdated CSIs. In this paper, we propose a different solution to improve the PDP estimates accuracy by employing multiple highly correlated PDP measurements, which performed by multiple cooperative vehicles. In our scheme, all cooperative vehicles are specially chosen, and the statistical characteristics of PDP might be viewed as highly approximate.

The paper is organized in the following way. In Section II, we give the description of the multi-user cooperative PDP estimation mode. In Section III, we propose the foundations of the linear interpolation estimator and introduce the PDP estimation algorithm based on user cooperation. The simulation and numerical result is presented in Section IV, and our conclusions in Section V.

2. MULTI-USER COOPERATIVE PDP ESTIMATION MODE

Fig. 1 illustrates our multi-user cooperative PDP estimation model. A V2I communication scenario is considered in a vehicular Ad Hoc networks (VANETs) arrangement, where the access point (AP) and vehicle receiver has only one antenna.

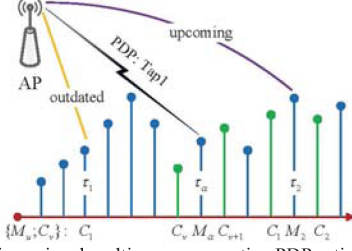


Fig. 1: A two-dimensional multi-user cooperative PDP estimation model: τ_1, τ_2 represent different delay times within the different multipath delay profile, the coordinate of M is (x_i, y_i) , and τ_α is the estimated delay spread of tap 1

As illustrated in Fig. 1, the master node M moves from M_1 to M_2 while, simultaneously, cooperation node C moves from C_1 to C_2 . Let $t = \{t_1, t_2, \dots, t_n\}$ denote the measurement times. Correspondingly, we can obtain two set of independent CIRs $h(x_i, y_i; t)$ and $h(x_j, y_j; t)$. Suppose that the radio channel is short-term stationarity, these two set of observations at the same location may be regarded as highly similar if M and C are moving at the same speed. We deduce that the estimated at current location might be refined by multiple historical measurements of this location.

Based on above assumption, let $\mathbf{S}_N = [S_1, S_2, \dots, S_N]^T$ be the vector of signals ($[\cdot]^T$ denotes matrix transpose). The OFDM symbol $\tilde{\mathbf{S}}_N$ can be represented as

$$\tilde{\mathbf{S}}_N = \mathbb{F}_N^{-1} \mathbf{S}_N \in \mathbb{R} \quad (1)$$

where \mathbb{F}_N^{-1} is an operator of N point inverse discrete Fourier transform (IDFT).

For master receiver at the u th location, we can write the received signal without noise as [7]

$$r_u(t) = \sum_{n=1}^L C_{n,u} \tilde{\mathbf{S}}_{n,u}(t - \tau_{n,u}) e^{j2\pi(f_c + f_{D,u})t + \phi_{n,u}} \quad (2)$$

Here $C_{n,u}, \phi_{n,u}, f_{D,u}, \tau_{n,u}$ are the amplitude, phase, Doppler frequency shift, and time delay, respectively, associated with the n th propagation path (L is the total number of paths).

In this paper, the V2I channel is modeled as a traditional FIR filter (tapped delay line implementation). Accordingly, the number of taps of the FIR filter is determined by the product of maximum excess delay and the system sampling rate. Then, the CIR at the location u can be further modeled as a linear time-variant filter whose complex baseband impulse is

$$h_u(t, \tau_u) = \sum_{n=1}^L C_{n,u} e^{j\phi_{n,u}(t)} \delta(\tau - \tau_{n,u}) \quad (3)$$

where $\delta(\cdot)$ is the Dirac delta function.

For simplification, suppose the time-varying CIR $h_u(t, \tau_u)$ is a zero-mean Gaussian random process satisfying the *wide-sense stationary uncorrelated scattering* (WSSUS) model. In equation (3), the complex amplitude $a_{n,u}(t) = C_{n,u} e^{j\phi_{n,u}(t)}$ may be regarded as a wide-sense stationary (WSS) complex Gaussian process that is independent for different paths with

$\mathbb{E}\left\{\left|C_{n,u} e^{j\phi_{n,u}(t)}\right|^2\right\} = C_{n,u}^2$. The statistical characteristics of the channel $h_u(t)$, namely the temporal auto correlation function of $\text{CORR}_u(\tau_u)$ is given by [8]

$$\begin{aligned} \text{CORR}_u(\tau_u) &= \mathbb{E}\{a_{n,u}(t - \tau_u) a_{n,u}^*(t)\} \\ &= C_{n,u}^2 J_0(2\pi f_{D,u} \tau_u) \end{aligned} \quad (4)$$

where $J_0(\cdot)$ is the zeroth-order Bessel function of the first kind, $f_{D,u}$ is the maximum Doppler frequency, and

the channel is normalized such that $\sum_{n=1}^L C_{n,u}^2 = 1$. Similarly,

the temporal auto correlation function of C_v can be represented as $\text{CORR}_v(\tau_v) = C_{n,v}^2 J_0(2\pi f_{D,v} \tau_v)$. We further have a better approximation

$$\lim_{f_{D_u} \rightarrow J_{D_v}, \tau_u \rightarrow \tau_v} \text{CORR}_u(\tau_u) = \text{CORR}_v(\tau_v) \quad (5)$$

(5) implies that joint estimation is mathematically tractable by using multi-user measurement, and it is reasonable to estimate $\hat{h}(x_\alpha, y_\alpha; t_k)$ from a set of observed data $h_v(t_k), v \in \{C_1, \dots, C_n, C_{(n+1)}, \dots\}$.

For mathematical simplicity, let $h(n, k)$ be the channel response in the specified position of the frequency-time grid, then the CIR at the n th tone of the k th OFDM block can be expressed as

$$h_u(n, k) = \sum_{i=0}^{L-1} a_{u,i}(n, k) \delta_{u,i}(n, k) e^{-j2\pi k M \tau_{u,i}} \quad (6)$$

$$h_v(n, k) = \sum_{i=0}^{L-1} a_{v,i}(n, k) \delta_{v,i}(n, k) e^{-j2\pi k M \tau_{v,i}}$$

In general, the PDP estimates can be directly calculated by the channel measurements, i.e., the sequence constitutes the average power delay profile (PDP) of the channel. Thus, we have

$$\mathbb{P}(t, \tau) = \mathbb{E}\{|h(t, \tau)|^2\} \quad \forall M_u, C_v \quad (7)$$

Clearly, the instantaneous PDP estimates at \mathbb{P}_u can be given as $\mathbb{P}_u^{(n)}(t, \tau) = |h_u(t, \tau)|^2$, and the PDP distribution is represented as a diagonal matrix $\text{diag}[\mathbb{P}_u^{(1)}, \mathbb{P}_u^{(2)}, \mathbb{P}_u^{(L)}]$.

Fig. 2 shows a snapshot of multi-user cooperative in a 4-lane one-way road. Meanwhile, a simple multi-user selection mechanism in practical VANETs is also illustrated, i.e., all surrounding cooperative vehicle terminals provide CSI to extract channel parameters for master vehicle terminal.

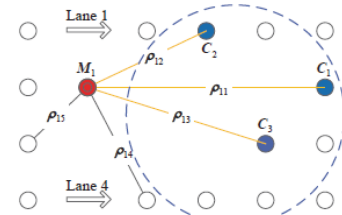


Fig. 2: A snapshot of multi-user cooperative PDP estimation model: $\rho_{ij}(t) = 1 - |v_p^i - v_q^j| / \max(v_p^i, v_q^j)$ is defined to identify the speed ratio of the i th vehicle and j th vehicle.

As shown in Fig.2, we further detail the cooperation user search and message transmission during the procedure of IVC-CE which can be summarized as follows:

Step 1: The master node M_1 initializes the cooperation request by transmitting an uplink message Msg_{REQ}^M (request message) to the AP. This message contains the current location (x, y) and the speed v_m^1 of the master node which can be used by the AP.

Step 2: Once the AP received Msg_{REQ}^M , it immediately generates a downlink message Msg_{BCCH} constituted by the master node's location, speed and the pre-defined minimum threshold ε . In this case, Msg_{BCCH} is *broadcast control channel* (BCCH).

Step 3: After received Msg_{REQ}^M , the receivers begin to calculate $\rho_{ij}(t)$ and $d_{CO}(t)$ at the current time. If there are one or more calculation results that meet (11) and (12), the corresponding receivers are considered candidate cooperation nodes. Next, the candidate nodes immediately report their location and speed to the AP by an uplink response message Msg_{REQ}^C .

Step 4: The AP is responsible for assigning the cooperation users and operating the IVC-CE procedures. The results of the assignment are broadcast to the vehicle receivers on the BCCH. The event of IVC-CE measurement involving single or multiple cooperation nodes is simultaneously triggered by the AP broadcast message Msg_{BCCH}^{SYS} .

Step 5: The AP periodically broadcasts the system message Msg_{BCCH}^{SYS} (e.g., 10s ~ 30s) to collect the mobility status information from the cooperation vehicles and transfers the related information to the next AP.

Remark 1: In steps 1, 3 and 5, we assume that each vehicle knows its position and velocity. In fact, the location, speed and direction can be achieved with low complexity real-time techniques by using on-board vehicle sensors, e.g., the motion direction and speed can be obtain from *steering wheel angle sensors* and *wheel speed sensors*, and the vehicle location can be collected by a low-cost GPS receiver, or a network-assisted positioning technique [12]. In addition, the steering wheel angle sensors might be helpful to predict the motion trends of the vehicle, e.g., driving in complex city street. To some extent, a large steering angle θ_{st} can simply be understood as an occasional cooperation interruption, which can be treated well and make a new attempt to recover cooperation. Therefore, IVC-CE technique is applicable to urban, suburban, and highway environments at a variety of speeds.

Remark 2: Fig. 2 also illustrates an optional cooperation user selection scheme, where the master vehicle is able to communicate with its direct neighbors or other remote vehicles. In this case, the master vehicle broadcasts the cooperation request Msg_{REQ} over a V2V channel to its

direct neighborhood, which also includes GPS location, velocity and minimum cooperation distance. In this case, the master vehicle is able to send its mobility status to the candidate nodes. The cooperation user selection occurs among vehicles and the result is in turn reported to the AP.

3. DERIVATION OF MULTI-USER PDP ESTIMATION

3.1 Quasi-static LMMSE Channel Estimation

Assume that a reference OFDM block in (1) is used to estimate the channel and all estimated channels $\tilde{h}(n, k)$ are Gaussian distributed and uncorrelated with the channel noise. For master nodes, the linear MMSE (LMMSE) algorithm can be written as [6]

$$\tilde{\mathbf{h}}_{u, LMMSE} = \mathbf{R}_{\tilde{h}_u, \tilde{h}_u} (\mathbf{R}_{\tilde{h}_u, \tilde{h}_u} + \frac{\beta_u}{snr_u} \mathbf{I}_u)^{-1} \mathbf{h}_{u, LS} \quad (8)$$

where \tilde{h}_u is the CIR at the pilot subcarriers, $\mathbf{h}_{u, LS}$ is the initial channel estimation carried out by the *least square* (LS) algorithm, $\mathbf{R}_{\tilde{h}_u, \tilde{h}_u}$ represents the cross-correlation between all the subcarriers and the pilot subcarriers, and $\mathbf{R}_{\tilde{h}_u, \tilde{h}_u}$ represents the auto-correlation between the pilot subcarriers. Here, \mathbf{I}_u is an identity matrix, $snr_u = \mathbb{E}(x_{u,i}^2) / \sigma_{u,n}^2$ is the average SNR.

The computational complexity of (8) can be further reduced by *singular value decomposition* (SVD) method [6], and can be calculated by

$$\mathbf{R}_{\tilde{h}_u, \tilde{h}_u} = \mathbf{U} \mathbf{\Lambda}_u \mathbf{U}^\dagger \in \mathbf{R}^{m \times m} \quad (9)$$

where the matrix \mathbf{U} is orthonormal and $\mathbf{U} \in \mathbf{R}^{m \times m}$, \mathbf{U}^\dagger is the Hermitian transpose and $\mathbf{\Lambda}_u$ is an $m \times m$ diagonal matrix with positive eigenvalues λ_k in descending order. Then (8) can be re-written as

$$\tilde{\mathbf{h}}_{u, LMMSE} = \mathbf{U} (\text{diag}[\delta_{u,i}]) \mathbf{U}^\dagger \mathbf{h}_{u, LS} \quad (10)$$

where $\delta_{u,i} = \lambda_i / (\lambda_i + \beta_u / SNR_u)$.

3.2 Multi-user interpolation PDP estimation

In this subsection, we indicate how to obtain the total power $\mathbb{P}(t, \tau)$ according to the derivation in Section II. Firstly, one can see that the amount of fading which can occur as a result of small changes in receiver locations, thus, linear fitting is reasonable to approximate the power of each tap that can be viewed as the log-normal or exponent distribution function. For the estimated \mathbb{P}_α at a particular location and a set of time and space-related measurements $\mathbb{P}_v^1(t, \tau), \mathbb{P}_v^2(t, \tau), \mathbb{P}_v^3(t, \tau), \dots$, the refined $\hat{\mathbb{P}}_\alpha(t, \tau)$ can be calculated by

$$\hat{\mathbb{P}}_\alpha(t, \tau) = \Psi [\mathbb{P}_v^1(t, \tau), \mathbb{P}_v^2(t, \tau), \mathbb{P}_v^3(t, \tau), \dots] \quad (11)$$

Without loss of generality, Ψ can be viewed as a function such as interpolation, polynomial fitting and so on, e.g., linear interpolation, a second order interpolation, low-pass interpolation, spline cubic interpolation [9].

A detailed description of the algorithm is as follows.

Step 1: As the estimated PDP is formed through time averaging of $\tilde{h}(t, \tau)$, for each M and C , and all the parameters $C_{n,u}$, $C_{n,v}$, $\tau_{n,u}$ and $\tau_{n,v}$ in (3) are estimated, we can calculate a coarse PDP estimate $\tilde{\mathbb{P}}_n(t, \tau)$. Accordingly, a set of coarse PDP estimates $\tilde{\mathbb{P}}_n(t, \tau)$ can be obtained, and it can be calculated by

$$\tilde{\mathbb{P}}_n(t, \tau) = \mathbb{E} \left\{ \left| \tilde{\mathbf{h}}_{n,LMSE}(t, \tau) \right|^2 \right\} \quad \forall M_u, C_v \quad (12)$$

Step 2: We fit the whole estimated PDP data using a set of interpolating base-functions $\{\Psi_1, \Psi_2, \dots, \Psi_n\}$. Let \mathbf{W}_n^u be the weighting coefficients of the fitted straight line. According to (11), we have the refined PDP estimates $\tilde{\mathbb{P}}_u(t, \tau)$ and $\tilde{\mathbb{P}}_v(t, \tau)$ as

$$\begin{cases} \tilde{\mathbb{P}}_u(t, \tau) = [\mathbf{W}_n^u]^H \Psi(\tilde{\mathbb{P}}_u(t, \tau)) \\ \tilde{\mathbb{P}}_v(t, \tau) = [\mathbf{W}_n^v]^H \Psi(\tilde{\mathbb{P}}_v(t, \tau)) \end{cases} \quad (13)$$

After substituting the refined PDP estimate $\tilde{\mathbb{P}}_v(t, \tau)$, the average PDP can be obtained based upon the individual PDP measurement performed at each local area.

Step 3: Considering the autocorrelation coefficient varies widely from indoor area to the outdoor area. The performance of PDP estimation should be further processed from the measurement data based on appropriate fitting criteria. To evaluate the performance of the PDP estimator, we adopt the *mean square error* (MSE) estimation criterion for practical observation position, which can be defined as

$$\mathbb{E} \left\{ \frac{1}{K} \sum_{k=1}^K \left| \tilde{\mathbb{P}}_u(t, \tau) - \mathbb{P}_u(t, \tau) \right|^2 \right\} \quad (14)$$

4. NUMERICAL RESULTS

In this section, the performance of the proposed PDP estimation approach for different system configurations and mobility conditions has been evaluated by extensive simulation.

Because there are no fading models defined in the 802.11p amendment/802.11 standard, we adopt the ITU-R M.1225 vehicular channel and COST 259 channel model to approximate the CIRs [10-11], where the maximum channel delay spread delay is $\tau_{max} = 800ns$ and the number of taps $L = 8$. Additionally, the parameters of average PDP and *Doppler spectral density* (DSD) are also used to set the original V2I channel.

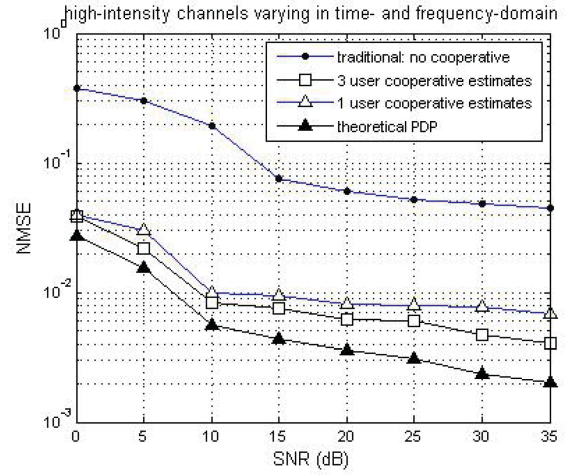


Fig. 3: PDP estimates performance: normalized MSE vs. SNR, 3 cooperative users and the master vehicle speed=90km/h

Fig. 3 shows the PDP estimation performance in terms of *normal mean square error* (NMSE), and an estimated PDP from a measurement is compared to a Monte Carlo simulated profile, respectively. The normalized MSE, here, is defined as the PDP estimation error, which is characterized as a complex Gaussian random variable with zero mean and a variance σ_e^2 . Furthermore, the MSE performance is simulated with different user cooperative conditions that are associated with the vehicle connectivity coefficient ρ_{ij} . In Figure 4, the average estimated PDP from the 50 Monte Carlo trials is displayed. A sample power delay profile is plotted, where the average power delay and the maximum excess delay ($\leq -70dBm = 400ns$) are all marked. From Figure 4, one can see that the proposed method has better estimation accuracy via cooperative measurements. Figs. 3 also illustrates that as the vehicle connectivity coefficient ρ_{ij} increases, the total estimation performance increases. It can be observed that $\rho_{ij} = 0.85$ is sufficient to achieve good performance and accuracy.

To further investigate the effectiveness of the proposed method, we consider a burst safety-critical data transmission model. The real-time safety-critical data are partitioned into different scheduling slots as $O(k)$, where k is the slot index. When we obtain a quasi-Static CSI or updating CSI fitted by multiple cooperative measurements, then, the optimal CSI $H(k)$ can be viewed to be updating channel knowledge within a scheduling slot, correspondingly, we can choose an optimal the scheduling slots $O^*(k)$. In return, $O^*(k)$ can be used to group multiple slots as a frame of duration T for reliable data transmission. Fig. 5 illustrates the BER performance in high speed scenarios, while the speed of mater vehicle is fixed as $120km/h$, and three cooperative vehicles are considered(at the beginning, the original speed is set as $120km/h$, $90km/h$ and $50km/h$). Fig. 5 also shows the various performance comparison of vehicle connectivity

coefficient ρ_{ij} . In high speed scenarios, we observe that the estimation performance is affected significantly by ρ_{ij} , and the optimal performance would be achieved when $\rho_{ij} \leq 0.9$.

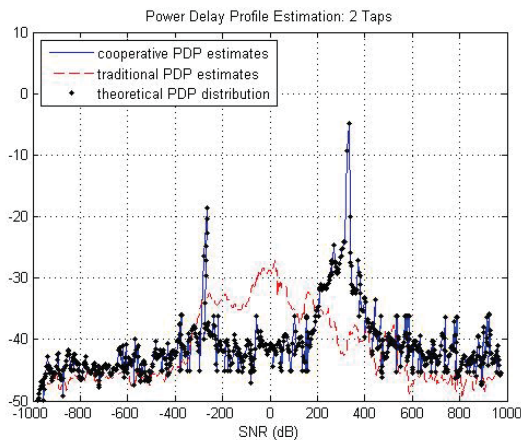


Fig. 3: Multi-user cooperative PDP estimates performance: 3 cooperative users and the master vehicle speed= 60km/h

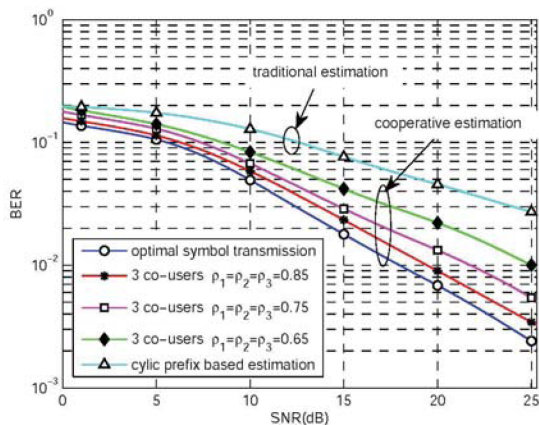


Fig. 4: BER performance with different PDP estimates: mater vehicle speed is 120km/h

5. CONCLUSION

This paper has presented an approach of multi-user cooperative PDP estimation for high-mobility IEEE802.11p V2I communications. To solve the outdated CSI problem, we have developed an effective interpolation estimation method that can yield accurate up-to-date channel estimation results. In particular, we have designed a reasonable channel estimation scheme to support scalable physical layer data transmission. Simulation and numerical results show that the proposed IVC-CE technique can enhance the channel estimation performance significantly and provide reliable safety-critical data transmission for various VANETs communication scenarios. We have developed an effective interpolation estimation method that can yield accurate up-to-date CSI estimation results in a high-mobility scenario, where the PDP estimates can be improved by a set of spatial-related observations. Simulation and numerical results show that the proposed approach can enhance the CSI estimation performance

significantly and provide reliable safety-critical data transmission for various vehicle communication scenarios.

ACKNOWLEDGMENTS

This work was supported from the China Scholarship Council, and in part by the research task of the State Key Laboratory of Rail Traffic Control and Safety (RCS2008ZT004), the key research task of the Ministry of Education of the Peoples Republic of China (Grant No. K13C800010), the National Natural Science Foundation of China (No.61372077), the fundamental Research Program of Shenzhen City(No. JC201005250067A/JCJY2012817163755061) and Guangdong Science and Technology Program (No. 2013B090200011).

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