

# Estimation of Lateral Displacement of Electric Vehicle to Wireless Power Transmitter in Dynamic Charging Scenario

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In dynamic charging scenario, electric vehicles continuously charge batteries while running on the wireless power transmitter-embedded road. According to past works, the relative position between the on-board receiver and transmitter affects efficiency and transmitted power. In this paper, a method for estimating relative position is proposed based on extended Kalman filter by updating the estimation with the measurement from the receiver when the measurement is available. This algorithm is verified by simulation and actual experiment with electric vehicle.

**Keywords:** Wireless power transfer, Dynamic charging, Electric vehicle, Extended Kalman filter

## 1. Introduction

Recently, Electric vehicles (EVs) are widely produced by several manufacturers. The main limitations of ongoing commercial EVs include high cost of large energy storage, inconvenience of plug-in charging process, limited range and long recharging time. Therefore, wireless power transfer (WPT) technology is introduced to EVs to solve these problems.<sup>(1)</sup>

Dynamic charging is a scenario that vehicle receives electric power while running on WPT transmitter-embedded road which allows EV to reduce the size of power storage, weight and the cost of power storage. As a result, EV could also continuously operate without long stopping for charging as it was implemented and demonstrated in Korea by KAIST.<sup>(2)</sup>

Vehicle positioning are the fundamental issues in the intelligent transportation system (ITS). Various sensors; for example, GPS, radar and vision sensor, are used for positioning purpose. However, each sensor has its own limitations. In the dynamic charging infrastructure, it is possible to obtain the relative position from a WPT receiver on the vehicle to the embedded transmitter. This can be an alternative way for vehicle positioning or used for improving the current positioning technology. In addition, for WPT issue, mutual inductance between the receiver and transmitter affects transmitted power and efficiency. However, The mutual inductance is varied as the vehicle moves. The relative position is also useful in vehicle position control to achieve the power demanded or high efficiency. This paper aims to estimate relative position to transmitters for vehicle position control.

The dynamics of relative position to a transmitter and receiver voltage characteristics are described in section 2. The estimator design is stated in section 3. The proposed algorithm is verified by simulation and experiment in section 4. and 5. respectively.

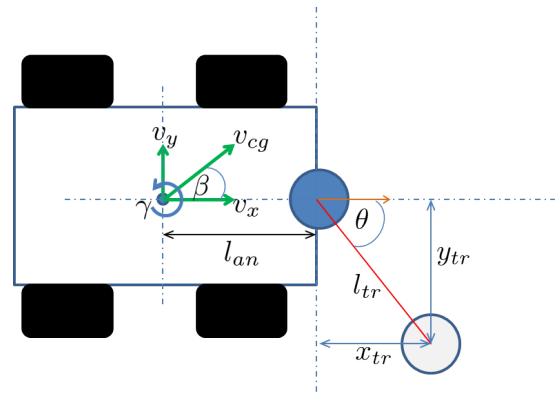


Fig. 1. Vehicle with WPT Model

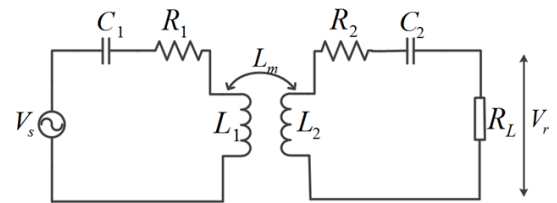


Fig. 2. WPT equivalent circuit

## 2. Vehicle Model with WPT Receiver

**2.1 Dynamic equation of relative position** A WPT receiver is rigidly fixed in front of a vehicle with a distance  $l_{an}$  from the CG point along longitudinal axis as shown in Fig. 1. The vehicle is moving with longitudinal velocity  $v_x$ , lateral velocity  $v_y$  and yaw rate  $\gamma$ . The effect of vibration and pitch angle causing the change in vertical gap is not considered in this paper.

The relative position of receiver to transmitter is expressed by two variables: displacement  $l_{tr}$  and orientation  $\theta$ . The longitudinal displacement to the transmitter  $x_{tr}$  is defined as

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$$x_{tr} = l_{tr} \cos \theta \dots \dots \dots (1)$$

and lateral displacement to the transmitter ( $y_{tr}$ ) is defined as

$$y_{tr} = l_{tr} \sin \theta \dots \dots \dots (2)$$

The goal of this paper is to continuously estimate lateral displacement ( $y_{tr}$ ) along the road.

Dynamic equation of the relative position is derived according to vehicle motion as

$$\dot{l}_{tr} = (v_y + \gamma l_{an}) \sin \theta - v_x \cos \theta \dots \dots \dots (3)$$

$$\dot{\theta} = \frac{(v_y + \gamma l_{an}) \cos \theta + v_x \sin \theta}{l_{tr}} + \gamma \dots \dots \dots (4)$$

**2.2 Voltage measurement** The equivalent circuit of WPT is shown in Fig. 2. Under the assumption of perfect resonance, the voltage across a constant load on the receiver side  $V_r$  is expressed as <sup>(3)</sup>

$$V_r = \left| \frac{\omega_0 L_m R_L}{R_1 R_L + R_1 R_2 + (\omega_0 L_m)^2} \right| V_s \dots \dots \dots (5)$$

where,  $V_s$  is voltage source.  $R_L$  is resistive load.  $R_1$  is resistance in transmitter system.  $R_2$  is resistance in receiver coil.  $L_m$  is mutual inductance.

The voltage measurement  $V_r$  depends only on mutual inductance between transmitter and receiver as  $V_s$ ,  $R_L$ ,  $R_1$  and  $R_2$  are constant. Moreover, the mutual inductance of spiral antenna with certain size and vertical gap depends only on the displacement  $l_{tr}$ . The mutual inductance of spiral antenna is calculated by method in <sup>(4)</sup>. The voltage measurement  $V_r$  is a function of displacement  $l_{tr}$  as shown in Fig. 3.

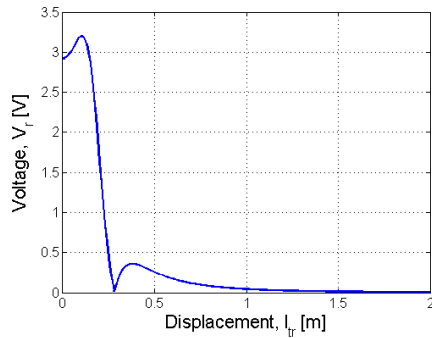


Fig. 3. Voltage-displacement characteristics

**3. Estimation Process**

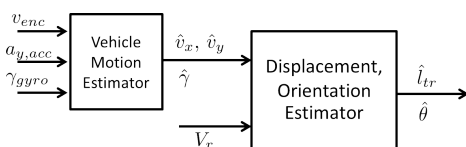


Fig. 4. Blockdiagram of estimation process

The WPT displacement and orientation estimation process is shown by block diagram in Fig. 4. This paper is focusing on the second block of relative position estimator which

employs vehicle motion input estimated from the first block while the measurement is the voltage measured across the load on receiver side  $V_r$ . The first block simply estimate vehicle motion from inertia measurement unit (IMU) through linear state observer.

By this cascaded architecture, the high computation cost is avoided and the state variables are possible to estimate even when the voltage measurement is unavailable.

The relative position estimation is dealing with nonlinear dynamic system. The extended Kalman filter is applied to solve this problem.

The filter problem always defines the system by two equation: process equation and measurement equation. In this paper, the state vector are including displacement and orientation  $x_k = [l_{tr,k} \theta_k]^T$ , the input is vehicle motion  $u_k = [v_x \ v_y \ \gamma]^T$  and the measurement is receiver voltage  $y_k = V_r$ . The process equation is obtained by discretizing equation (3) and (4) by the forward Euler method as

$$l_{tr,k+1} = l_{tr,k} + T_s [(v_{y,k} + \gamma_k l_{an}) \sin \theta_k - v_{x,k} \cos \theta_k] \cdot (6)$$

$$\theta_{k+1} = \theta_k + \left[ \frac{(v_{y,k} + \gamma_k l_{an}) \cos \theta_k + v_{x,k} \sin \theta_k}{l_{tr}} + \gamma_k \right] \cdot (7)$$

while the measurement directly utilizes the mapping of the voltage-displacement characteristics shown in Fig. 3.

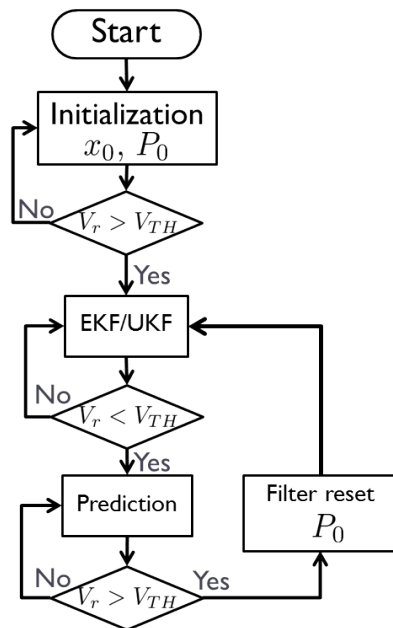


Fig. 5. Algorithm for estimation with multi-transmitter system

The algorithm for estimating relative position in the dynamic charging scenario is shown in Fig.5. Firstly, the estimation is held until the reliable voltage data received. In this paper, the unreliable measurement is the measurement of voltage lower than threshold voltage ( $V_r < V_{th}$ ) where  $V_{th} = 1.3$  V. The driver must control the vehicle close enough to transmitters to initiate the estimation. Then, if reliable voltage is received, the algorithm will estimate based on EKF. On the other hand, if the received voltage is determined to be

unreliable, the estimation will be based only on prediction process according to the estimated vehicle motion from IMU sensors. Then, if voltage becomes reliable again, it means that the receiver already moves closer to the next transmitter. The algorithm will reset the covariance matrix and resume estimating by EKF.

#### 4. Simulation

In the simulation, the vehicle moves with constant longitudinal velocity  $v_x = 1$  m/s and steering angle  $\delta = -0.003, 0.001$  rad at  $t = 2, 8$  s respectively causing the lateral velocity and yaw rate as shown in Fig. 6(b) and Fig. 6(c) respectively. The distance between each transmitter is 4 m. In Fig. 6(a), the trajectory of vehicle is shown moving forward to the transmitter line. As a result, the received voltage is measured as in Fig. 6(d). In Fig. 6(d)(e)(f)(g), the red shaded area indicates reliable measurement and the estimation is updated by EKF while the unshaded area corresponds to unreliable measurement only prediction based on vehicle motion is applied.

The estimation of state variables are shown in Fig. 6(e)(f). When the receiver passes through the first transmitter, the estimator would be still on hold since the receiver does not reach the region of reliable measurement. From the second transmitter, the estimator applies EKF shown in red shaded area. Then, the prediction is only applied when voltage measurement is unavailable. When the receiver reach third transmitter, the EKF is applied again causing the sudden change in the estimation because the reference transmitter is shifted from the second transmitter to third transmitter. The blue line is the actual state variables while the red line is obtained from the proposed algorithm. This method could correctly estimate the trend of lateral displacement in the dynamic charging system. However, the estimation is not smooth enough when the reference transmitter is shifted therefore this estimation is still not suitable for position control.

#### 5. Experiment



Fig. 7. Experiment setup for multi-transmitter system

The WPT receiver is attached in front of an electric vehicle COMS manufactured by Toyota Auto Body Co., Ltd. A RT-linux computer is applied to collect and process data from sensors. The distance between each transmitter is 4 m.

Vehicle manually passes transmitters with the lateral displacement less than 15 cm to the center of transmitter line and tends to move closer to the transmitter line. The inputs of

estimation obtained from vehicle motion estimator are shown in Fig. 8(a)(b)(c). The voltage measurement is shown in Fig. 8(d). The state estimation results are shown in Fig. 8(e)(f). The EKF is applied in the red shaded area meaning that the receiver moves forward to the transmitter. The estimation of lateral displacement in Fig. 8(g) is always less than 15 cm and moves forward to the transmitter line in each transmitter verifying the correctness of the proposed method. As the results, the estimation is not smooth enough when the reference transmitter is shifted as the simulation indicated.

#### 6. Conclusion

This paper proposed a method to estimate lateral position to the transmitter in dynamic charging scenario using EKF by applying updating process in case of reliable measurement and only prediction process in case of unreliable measurement. From the results, the proposed method could correctly estimate the trend of vehicle lateral displacement. However, the limitation is that it cannot provide the smooth estimation when the reference transmitter is shifted; therefore, the result cannot be directly utilized for the position control. The interpolation algorithm should be implement for smoothing the data before employing it for position control.

#### References

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#### Appendix

##### 1. Extended Kalman filter algorithm

###### 1. Prediction process:

###### 1.1 State prediction

$$\hat{x}_k^- = f(x_{k-1}, u_{k-1})$$

###### 1.2 Output prediction

$$\hat{y}_k = h(\hat{x}_k^-)$$

###### 1.3 Covariance prediction

$$P_k^- = AP_{k-1}A' + Q$$

###### 1.4 Cross covariance prediction

$$R_{xy} = P_k^- C^T$$

###### 1.5 Output covariance prediction

$$R_y = CP_k^- C^T + R$$

###### 2. Correction process:

###### 2.1 Kalman gain

$$K = R_{xy}R_y^{-1}$$

###### 2.2 State correction

$$\hat{x}_k = x_k^- + K(y_k - y_k^-)$$

###### 2.3 Covariance correction

$$P_k = (I - KC)P_k^-$$

where  $A = \frac{\partial f}{\partial x}|_{(\hat{x}_{k-1}, u_{k-1})}$ ,  $B = \frac{\partial f}{\partial u}|_{(\hat{x}_{k-1}, u_{k-1})}$ ,  $C = \frac{\partial h}{\partial x}|_{(\hat{x}_{k-1})}$

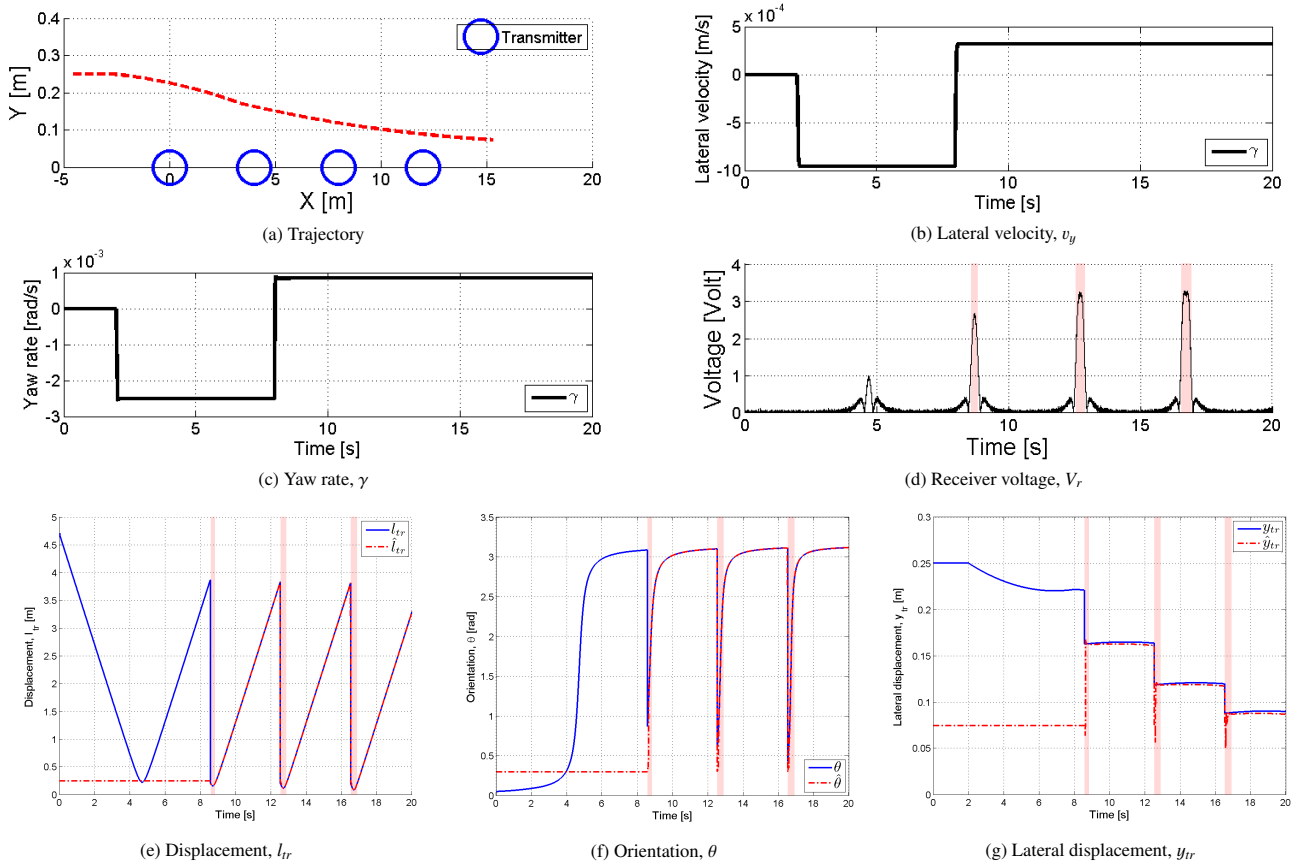


Fig. 6. Simulation result

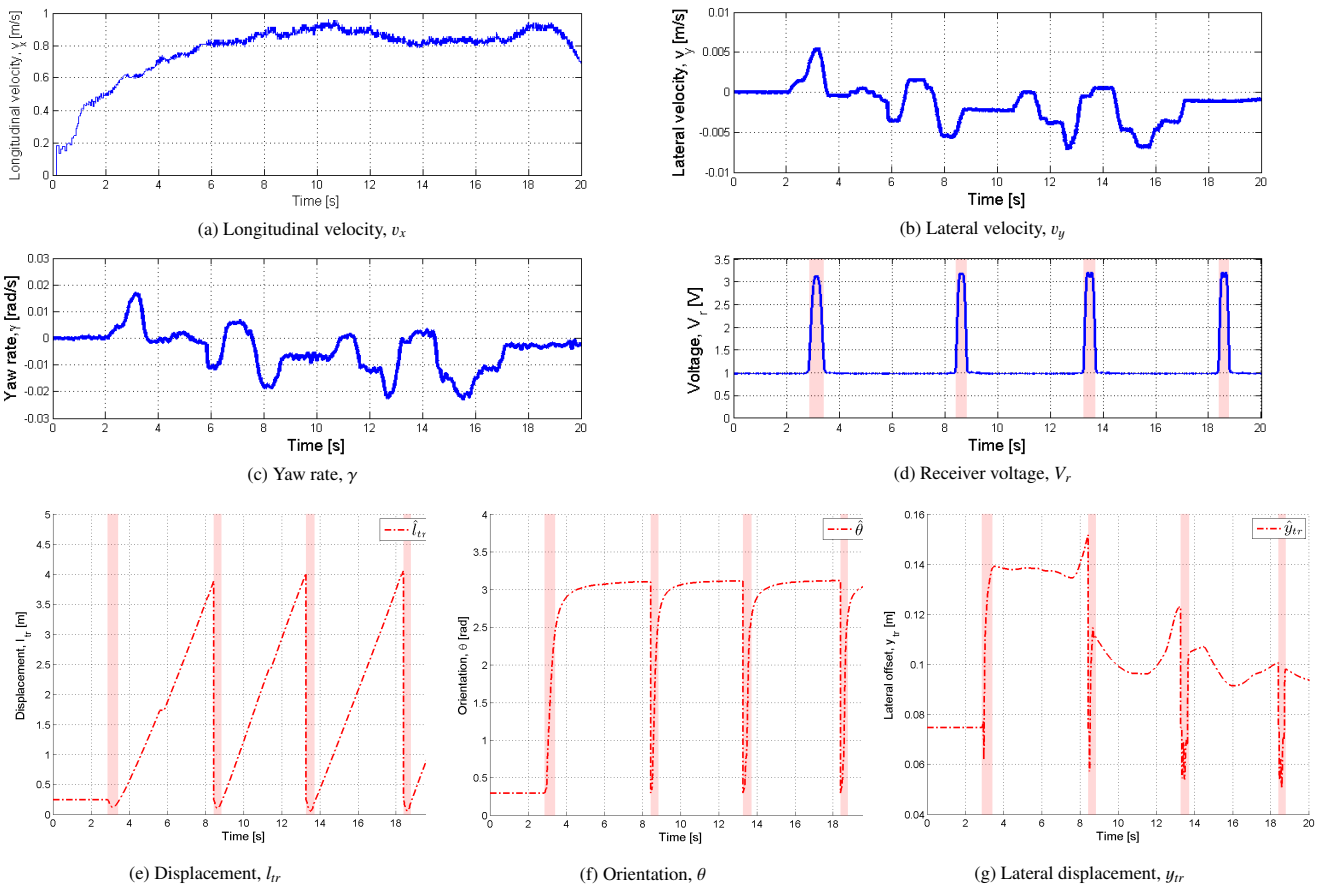


Fig. 8. Experiment result