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Target torque estimation for gearshift in dual clutch transmission with uncertain parameters[☆]

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ABSTRACT

The target torque of engaging clutches during gearshift is a key factor that affects the dynamic response of powertrains equipped with the dual clutch transmissions (DCT). This paper investigates a method to estimate the target torque of engaging clutches under conditions where engine torque and measurement signals contain white noise and some vehicle parameters (the radius of wheel and rolling friction coefficient) are uncertain. To compute the target torque accurately, the state of system should be estimated when the uncertain parameters exist. The vehicle powertrain is modeled as the 3DOF system when one clutch is closed and the 4DOF system when two clutches are open, while the measured signals include speeds of the engine, transmission, and vehicle (rotational speed of wheels). In addition to traditional extended Kalman filter (EKF), both the joint extended Kalman filter (JEKF) and dual extended Kalman filter (DEKF) are used to estimate the target torque. The simulation results show that DEKF and JEKF provide much higher accuracy in the estimation of target torque than EKF when some parameters of the model are uncertain, so as to produce a better ride performance of the transmission during gearshift, i.e. reduction of power interruption and compressed shifting time. Furthermore, the DEKF provides higher accuracy than the JEKF in estimating uncertain parameters.

1. Introduction

Vehicle transmission systems have a significant influence on the dynamic performance of automobiles. Several types of transmission systems have been developed in automotive engineering, such as the manual transmission (MT) [1], automated manual transmission (AMT) [2], planetary automatic transmission (AT) [3], continuously variable transmission (CVT) [4], and dual clutch transmission (DCT) [5]. DCT equipped powertrains combine the power-on shifting capabilities of AT and CVT, with the high-efficiency components of MT, such as gears and synchronizers [6]. Gearshift transients are the result of discontinuities of speed, torque, and inertia in the transmission. Due to the nature of DCTs, the stepped change in inertia cannot be avoided, so the control of speed and torque in the engine and clutches is very important. Additionally, DCTs and ATs at higher gear ratios do not rely on fluid couplings, such as torque converters, and therefore the damping present in such transmission is significantly reduced, which increases the difficulty for suppressing transients. Therefore high-quality

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shift control of DCTs is required to perform clutch-to-clutch gearshifts without loss of tractive load, while still providing comfort and ride quality equivalent to conventional ATs.

An analytical model for the simulation, analysis, and control of shift dynamics for DCT equipped vehicles is presented in reference [7], which also investigates the variation in output torque in response to different clutch pressure profiles during shifts. Galvagno et al. [8] study the transmission kinematics and dynamics of a DCT, considering the possible configurations that can take place to the various power flow paths. Walker et al. [9] propose a method that combines speed and torque control of both engine and clutches to control gearshifts for vehicle powertrains equipped with wet DCTs, in which a detailed clutch hydraulic model is included. Powertrain control is realized through control of clutch solenoids and manipulation of the engine throttle input. To study the influence of engine torque harmonics, model degrees of freedom, and dual mass flywheels on the transient response of a vehicle equipped with a DCT, dynamic models are extended to include an engine model with torque harmonics and the addition of a dual mass flywheel to study the impact on powertrain response [10]. Reference [6] proposes an approach for active suppression of transient responses utilizing only the current sensors available in the powertrain with DCT. An active control strategy for manipulating engine or electric machine output torque post gear change via a PID controller is developed and implemented. Liu et al. [11] analyze gearshift processes by modeling and simulation. The control strategies for both the torque phase and the inertia phase of both clutches are proposed, by controlling the engine torque and clutch torque. Research of synchronization process in wet DCT is performed in [12], where the clutch drag torque is analyzed. An online estimation method for drag clutch is proposed and then is applied to develop a supervisor control strategy. An optimal control based on the minimum principle is proposed in [13] to solve the problems with the starting process of a five-speed dry DCT. During the slipping phase, the minimum principle and improved engine constant speed control are adopted to obtain the optimal clutch and engine torques and their rotating speeds, with the minimum jerk intensity and friction work as optimization objectives.

As aforementioned, estimation of the torque in clutches for DCT control is critical to achieving high-quality control during the gearshift. In real vehicles, it is difficult to measure the torque on a rotating axle using direct torque measurement, such as with wireless torque sensors, and also expensive. Thus the use of such sensors in practice is not common. Using available sensors existing in the vehicle is much more practical, which can include the use of measured velocity through wheel, transmission and engine speed sensors to estimate torque is a more desirable method. It is worth noticing that noise cannot be avoided in measurement signals, particularly for hybrid and electric vehicle systems where electro-magnetic interference (EMI) arising in power converters (i.e. gate drives) is a significant issue for real vehicles. However, models used in the previously papers were based on the assumption that all signals (both input and output) are ideal. To make the shift process more stable, any noise existing in real systems should be replicated in models used for model based control development. At the same time, many parameters are uncertain (or unknown) in a real vehicle, e.g. the radius of the wheel may change with the loads and tire pressure, the tire rolling friction coefficient [14,15] also changes with the road conditions. Therefore, it is necessary to estimate the torque to control the gearshift of DCT with uncertain parameters.

When some form of noise is included in the dynamic models or measurement signals, methods for state estimation should be employed to obtain the actual states of a system. The subject of state estimation of a partially observed dynamic system in a stochastic frame has been studied by many scientists and there are well developed algorithms to manage the state-space models [16]. For the linear dynamic systems, the Kalman filter [17] is the most popular method. The Kalman filter combines the prediction of dynamic model and noisy measurement to estimate the state variables, which provides more accurate states estimation than both model prediction and noisy measurement alone.

To solve nonlinear dynamic systems, the Kalman filter is extended by using linearization procedures, termed as extended Kalman filter (EKF) [18–22]. Aside from EKF, other types of filters are also developed to solve the dynamic systems with high nonlinearity, e.g. the particle filter (PF) and unscented Kalman filter (UKF) [21,23–25]. Compared to EKF, the PF and UKF are applicable to highly nonlinear systems with non-Gaussian uncertainties, but they are computationally expensive [16]. UKF has been used in state estimation of vehicle dynamics. [26] presents a computational method based on UKF algorithm to estimate both longitudinal and lateral velocities and develops a novel quasi-stationary method to predict normal tire forces of heavy trucks on a sloping road. Boada et al. [27] also use UKF to estimate the sideslip angle to control the vehicle dynamics and improve its behavior. Zhao et al. [28] build a model of a DCT vehicle powertrain system and estimate the torque transmitted by a twin clutch during the up shifting process based on UKF. The torque estimation algorithm is verified using a DCT prototype vehicle installed with torque sensors on the drive half-shafts.

Aside from state variables, some unknown parameters in dynamic systems may also need to be estimated since they may be not known precisely. EKF can be used to estimate the parameters of a model directly, but clean training data of input and output variables are required [29], which means there must be no noise in the model or measurement signals. Vahidi et al. [14] use recursive least squares (RLS) with multiple forgetting factors to estimate the vehicle mass and road grade. RLS does not contain the prediction step, which is different from Kalman filters. The estimation of both states and parameters is investigated in [30,31], but it is used to solve linear dynamic systems only. When both the state variables and unknown parameters of a nonlinear dynamic model are required to be estimated, the joint extended Kalman filter (JEKF) [32] and dual extended Kalman filter (DEKF) [33] are usually used. JEKF combines both state variables and unknown parameters in a joint state-space representation, the unknown parameters are treated as additional state variables, and then the traditional EKF is used. DEKF uses two Kalman filters concurrently: one for states estimation, and the other for parameters estimation [29]. The Kalman filter is also associated with PF to estimate the state variables and unknown parameters [34].