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RESEARCH ARTICLE

A Novel Data-Driven MPC Framework Using KDE and KPCA for Autonomous Vehicles

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ABSTRACT Modeling and controlling complex, nonlinear, large-scale systems such as autonomous vehicles presents significant challenges due to high dimensionality, uncertain dynamics, and real-time constraints. This paper introduces a novel data-driven predictive control framework that synergistically integrates Kernel Density Estimation (KDE), Kernel Principal Component Analysis (KPCA), and Hankel matrix representation to address these challenges. The Hankel matrix formulation captures temporal correlations in system dynamics, enabling an effective representation of state transitions and dynamic modes. This representation is complemented by KPCA for nonlinear dimensionality reduction and KDE for probabilistic uncertainty quantification, resulting in a comprehensive framework that maintains computational tractability without sacrificing model fidelity. We present a rigorous mathematical foundation for the integration of these techniques, establishing formal convergence guarantees and error bounds for the kernel-based approximations. The framework demonstrates remarkable efficiency in feature extraction, preserving 95% of system variance with only two principal components, while the KDE component provides robust probabilistic predictions essential for safe autonomous navigation. Extensive experimental validation on an autonomous vehicle platform yields outstanding performance metrics: lateral tracking errors of 0.0225 m (RMSE), heading errors of 0.0476 rad, and longitudinal velocity tracking errors of 0.2725 m/s. These results represent an 81.3–89.8% improvement over traditional MPC approaches across diverse operational scenarios, including urban navigation, highway driving, parking maneuvers, and obstacle avoidance. The computational efficiency of our approach (1.6 ms execution time) enables real-time implementation on standard automotive-grade embedded control units while maintaining 100% compliance with lateral safety constraints. Comprehensive comparative analysis against state-of-the-art methods demonstrates that our framework effectively addresses the fundamental challenges of nonlinearity, high dimensionality, uncertainty quantification, and real-time implementation in autonomous vehicle control. These contributions advance the field of data-driven control for complex, nonlinear, large-scale systems, offering a principled alternative to traditional model-based approaches with significant practical implications for autonomous driving technologies.

INDEX TERMS Kernel-based predictive control, nonlinear and large-scale systems, kernel density estimation, kernel PCA, Hankel matrix, autonomous vehicles.

NOMENCLATURE

STATE VARIABLES AND VECTORS

x_k	State vector at time step k.
u_k	Control input at time step k.
y_k	System output at time step k.
w_k	Process disturbances.
v_k	Measurement noise.
$x_{k+i\|k}$	Predicted state i steps ahead from time k.
$u_{k+i\|k}$	Predicted control input i steps ahead from time k.
$\Delta u_{k+i\|k}$	Input rate of change.

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$x_{\text{ref}}, u_{\text{ref}}$	Reference trajectories.
$x_{\min}, x_{\max}$	State constraints.
$u_{\min}, u_{\max}$	Input constraints.
$\Delta u_{\min}, \Delta u_{\max}$	Rate constraints.

VEHICLE-SPECIFIC VARIABLES

x_p, y_p	Position coordinates of the vehicle.
θ	Orientation (yaw angle) of the vehicle.
v_x	Longitudinal velocity.
v_y	Lateral velocity.
ω	Yaw rate.
a	Applied acceleration.
δ	Steering angle.
F_{yF}	Front lateral tire force.
F_{yR}	Rear lateral tire force.
l_f	Distance from center of gravity to front axle.
l_r	Distance from center of gravity to rear axle.
m	Vehicle mass.
I	Vehicle moment of inertia.
e_{lat}	Lateral error.
e_{lon}	Longitudinal error.

COST FUNCTION AND OPTIMIZATION

$J(x_k, U)$	Cost function.
N	Prediction horizon.
Q, R, S	Weighting matrices.
$V_f(x_{k+N\|k})$	Terminal cost.
$g(x_k, u_k)$	Nonlinear constraints.
U_k	Control sequence.

MACHINE LEARNING METHODS

$\Phi(x)$	Feature mapping function.
$\mathcal{F}$	Feature space.
$k(x_i, x_j)$	Kernel function.
K	Kernel matrix.
K_h	Kernel function with bandwidth h.
λ	Eigenvalues.
v	Eigenvectors.
H	Bandwidth matrix.
$\|H\|$	Determinant of bandwidth matrix.
$\hat{f}(x)$	Kernel density estimate.
$p(x_{k+1}\|x_k, u_k)$	Conditional density estimate.
$\hat{p}$	Estimated probability density.
$\|\hat{f} - f\|_\infty$	Supremum norm.
$\mathbb{E}[x]$	Expected value of x.
Σ_{k+1}	Covariance matrix.
α	Confidence level parameter.
ϵ	Error threshold.
c	Constant (in probability bounds).
h_n	Bandwidth parameter.
O_p	Convergence in probability notation.
O	Big O notation.

HYBRID AND ADVANCED CONTROL

u_{MPC}	Model-based control component.
u_{RL}	Reinforcement learning control component.
π_θ	Learned policy with parameters θ.
$\mathcal{W}$	Bounded uncertainty set.
$\mathcal{Z}$	Uncertainty tube.
$\hat{x}_k$	Estimated state.
$\mathcal{X}_k$	State tube.
f_{NN}	Neural network function approximator.
$f_{\text{KDE, KPCA}}$	Learned model based on KDE and KPCA.
Ψ	Lifting function.
K	Koopman operator.
$\hat{J}_n$	Expected cost using estimated model.
J^*	Optimal cost.

MATHEMATICAL OPERATORS AND SETS

$\mathbb{R}^n$	n-dimensional real vector space.
$\mathbb{P}$	Probability measure.
$\oplus$	Minkowski sum.
$\mathcal{H}$	Reproducing kernel Hilbert space.
$\langle \phi(x_i), \phi(x_j) \rangle_{\mathcal{F}}$	Inner product in feature space.
$\|\cdot\|_Q$	Weighted norm with matrix Q.
$\mathcal{N}_i$	Neighborhood set.
RMSE	Root Mean Square Error.
MISE	Mean Integrated Squared Error.

I. INTRODUCTION

The control of complex nonlinear large-scale systems, particularly in the domain of autonomous vehicles, presents significant challenges in modern control engineering. These systems exhibit inherent nonlinearities, high dimensionality, and complex dynamics that defy accurate modeling using traditional methods. The difficulty is further compounded by dynamic uncertainties, environmental variations, complex interactions between system components, time-varying parameters, unpredictable disturbances, and system degradation over time. In autonomous vehicles, these challenges are especially pronounced due to the necessity of real-time decision-making, safety-critical operations, and the need to handle diverse driving scenarios.

Model Predictive Control (MPC) has emerged as a promising approach for nonlinear large-scale systems due to its ability to handle constraints and optimize performance over a prediction horizon. However, conventional MPC approaches for such systems face several critical limitations. As highlighted by [1], computational complexity grows exponentially with system dimension, creating a significant barrier for real-time implementation in high-dimensional spaces. Additionally, [2] note that traditional MPC formulations struggle with the dual challenge of model inaccuracies and uncertainty quantification in nonlinear large-scale contexts.

The application of MPC to nonlinear large-scale systems has seen various approaches in recent literature. Reference [3] proposed distributed MPC architectures that decompose large-scale systems into manageable subsystems, but these

approaches often sacrifice global optimality and struggle with coordination between subsystems. Reference [4] introduced adaptive MPC frameworks that can adjust to changing system parameters, yet these methods typically require explicit system models that are difficult to obtain for complex nonlinear systems. Reference [5] explored hybrid MPC-Reinforcement Learning approaches, which show promise but lack rigorous stability guarantees when scaling to large-scale applications.

Despite these advances, a significant research gap exists in the development of MPC frameworks specifically designed for nonlinear large-scale systems that can simultaneously: efficiently handle high-dimensional state spaces without prohibitive computational burden, accurately capture complex nonlinear dynamics without requiring extensive analytical modeling, rigorously quantify and manage uncertainties with formal stability guarantees, and enable real-time implementation in safety-critical applications such as autonomous vehicles.

Data-driven methods for nonlinear system control have evolved as potential solutions to address this gap. Direct data-driven control methods, as investigated by [6], utilize input-output data without explicit system identification, while Virtual Reference Feedback Tuning (VRFT) proposed by [7] designs controllers based on experimental data in a single trial. However, these approaches have not been effectively integrated into MPC frameworks for large-scale nonlinear systems, particularly where safety guarantees are paramount.

The integration of machine learning techniques with MPC for nonlinear large-scale systems presents another promising direction, though with its own challenges. Neural Network-based control can represent complex dynamics, but often lacks interpretability and requires large datasets for training. Kernel methods offer a middle ground with theoretical guarantees, but their application in MPC for high-dimensional nonlinear systems remains underdeveloped. The fundamental challenge lies in balancing model accuracy, computational efficiency, and theoretical guarantees when scaling to large, complex systems.

To address this research gap, this paper proposes a novel data-driven MPC framework specifically designed for nonlinear large-scale systems that integrates advanced statistical learning techniques. The proposed framework leverages Kernel Density Estimation (KDE) for nonparametric estimation of state transition probabilities and Kernel Principal Component Analysis (KPCA) for nonlinear dimensionality reduction, which together enable effective modeling of complex system dynamics while maintaining computational tractability. Using these methods within the MPC framework, we overcome the limitations of traditional approaches in handling nonlinearities, high-dimensional data, and uncertainties in large-scale systems.

The framework's development is supported by Lyapunov-based stability analysis, which guarantees stability under both nominal and perturbed conditions, while also providing explicit bounds on prediction errors. The implementation emphasizes computational efficiency through sparse kernel approximations and optimization techniques, making it suitable for real-time applications in high-dimensional spaces. The effectiveness of the framework is demonstrated through extensive simulations of large-scale autonomous vehicle systems, showcasing its ability to achieve robust, high-performance control across diverse, safety-critical driving scenarios.

In summary, this research introduces an innovative approach to nonlinear large-scale system control by combining advanced machine learning techniques with MPC. The proposed data-driven MPC framework addresses the key challenges and research gaps in controlling high-dimensional nonlinear systems, providing a flexible, adaptive solution capable of real-time performance with formal stability guarantees.

The remainder of this paper is structured as follows: Section II outlines the key techniques, including Hankel matrix formulation, KPCA, and KDE, along with their theoretical foundations for modeling nonlinear large-scale systems. Section III presents our proposed data-driven MPC paradigm that integrates these techniques, with an emphasis on convergence properties and error bounds. Section IV explores the application of our framework to autonomous vehicle control, serving as a case study for complex nonlinear large-scale systems, and details our bicycle model implementation and control problem formulation. Section V provides comprehensive experimental results across multiple driving scenarios, including comparative analyses with state-of-the-art methods. Finally, Section VI concludes the paper and discusses potential directions for extending our kernel-based framework.

II. BACKGROUND AND RELATED WORK

A. OVERVIEW OF MODEL PREDICTIVE CONTROL (MPC)

Model Predictive Control (MPC) has emerged as a powerful framework for controlling nonlinear systems, with significant developments in both theoretical foundations and practical applications [8], [9]. The fundamental principle of MPC lies in its ability to solve an optimal control problem over a finite prediction horizon, implementing only the first control input and repeating the optimization at each sampling instant. Model Predictive Control (MPC) is formulated as an optimization-based control strategy that predicts system behavior over a finite horizon. The fundamental components of nonlinear MPC include system dynamics, cost function, and constraints [8].

The nonlinear system dynamics are described by:

$$x_{k+1} = f(x_k, u_k, w_k) \tag{1}$$

$$y_k = h(x_k, v_k) \tag{2}$$

where:

- $x_k \in \mathbb{R}^n$ is the state vector at time step k
- $u_k \in \mathbb{R}^m$ is the control input

- $y_k \in \mathbb{R}^p$ is the system output
- w_k represents process disturbances
- v_k represents measurement noise

The MPC optimization objective is defined by the cost function:

$$J(x_k, U) = \sum_{i=0}^{N-1} \left\| x_{k+i|k} - x_{\text{ref}} \right\|_Q^2 + \left\| u_{k+i|k} - u_{\text{ref}} \right\|_R^2 + \left\| \Delta u_{k+i|k} \right\|_S^2 + V_f(x_{k+N|k}) \quad (3)$$

where:

- N is the prediction horizon
- x_{ref} and u_{ref} are reference trajectories
- Q, R, and S are weighting matrices
- $V_f(x_{k+N|k})$ is the terminal cost
- $\Delta u_{k+i|k}$ represents the input rate of change

The optimization is subject to the following constraints:

$$x_{\min} \leq x_k \leq x_{\max} \text{ (State constraints)} \quad (4)$$

$$u_{\min} \leq u_k \leq u_{\max} \text{ (Input constraints)} \quad (5)$$

$$\Delta u_{\min} \leq \Delta u_k \leq \Delta u_{\max} \text{ (Rate constraints)} \quad (6)$$

$$g(x_k, u_k) \leq 0 \text{ (Nonlinear constraints)} \quad (7)$$

The implementation challenges of nonlinear MPC have been extensively studied, with particular focus on computational efficiency and real-time applications. Recent advances in algorithms and computing hardware have made it possible to apply MPC to increasingly complex systems with faster dynamics [10]. Moreover, the integration of learning-based methods has opened new possibilities for handling model uncertainties and improving control performance [11].

B. CHALLENGES IN NONLINEAR SYSTEM MODELING

Modern control theory faces significant challenges in modeling and controlling nonlinear systems due to their inherent complexity. Recent research has focused on integrating multiple methodologies to address these challenges effectively, as traditional modeling approaches often struggle with nonlinear system identification due to system complexity, high dimensionality, time-varying parameters, uncertainties, complex interactions between subsystems, and environmental disturbances [12].

Building upon the basic MPC formulation presented in equations (1)–(7), the integration of kernel-based methods with traditional control theory has shown promising results, particularly through the kernel-based data-driven predictive control for autonomous vehicle path following [12]. In this framework, the control input can be formulated using kernel methods to address nonlinearities:

$$u_k = u_{\text{model}} + u_{\text{kernel}} \quad (8)$$

$$u_{\text{kernel}} = \sum_{i=1}^{N_s} \alpha_i K(x_k, x_i) \quad (9)$$

where $K(x_k, x_i)$ represents a kernel function and α_i are learned weights. This approach enhances the basic control structure defined in equation (1) by incorporating data-driven components. Building upon this foundation, probabilistic approaches using KDE provide a systematic framework for managing model uncertainties [13]:

$$p(x_{k+1}|x_k, u_k) \approx \frac{1}{Nh^d} \sum_{i=1}^{N} K\left(\frac{x_{k+1} - f(x_k^i, u_k^i)}{h} \right) \quad (10)$$

$$\mathcal{X}_k = \{x : p(x|x_k, u_k) \geq \delta\} \quad (11)$$

This approach explicitly accounts for uncertainties through probabilistic modeling, extending the uncertainty handling capabilities beyond the basic formulation in equations (1)–(2)

For dimensionality reduction in nonlinear MPC, Kernel Principal Component Analysis (KPCA) offers an effective approach [14], representing complex systems as:

$$\phi(x_k) = \sum_{i=1}^{r} \alpha_i K(x_k, x_i) \quad (12)$$

$$\tilde{x}_k = W^T \phi(x_k) \quad (13)$$

This formulation transforms high-dimensional nonlinear systems into lower-dimensional representations, providing a tractable approach to nonlinear system representation that complements the original MPC formulation in equations (1)–(2).

For large-scale nonlinear systems, interpretable data-driven approaches have emerged as scalable solutions [15]:

$$x_{i,k+1} = \sum_{j=1}^{r} \beta_j K(z_{i,k}, z_j)[A_j x_{i,k} + B_j u_{i,k} + \sum_{l \in \mathcal{N}_i} G_{jl} x_{l,k}] \quad (14)$$

These approaches have shown significant improvements in various applications. As shown in Table 1, kernel-based methods have demonstrated substantial performance gains across different autonomous vehicle applications, with improvements ranging from 15-30% depending on the specific domain and control objectives.

TABLE 1. Performance improvements in different applications.

Domain	Gain	Metric
Autonomous Vehicle Control	15-20%	Tracking Performance [12]
Connected Vehicles	25%	Energy Efficiency [15]
Adverse Weather Driving	30%	Control Robustness [16]

However, several challenges remain, including computational complexity that increases exponentially with system dimension, integration challenges in combining multiple modeling approaches while maintaining stability guarantees (particularly when combining equations (8)–(14) with the basic MPC framework defined by (1)–(7)), and real-time implementation constraints for high-dimensional systems [10].

Current research directions focus on developing more efficient computational methods, enhanced uncertainty quantification techniques (building upon equations (10)–(11)), improved integration of data-driven and model-based approaches (as shown in equations (8)–(9)), and scalable solutions for high-dimensional systems [17]. This evolution in nonlinear system modeling suggests a trend toward hybrid approaches that combine classical modeling techniques with modern kernel-based methods, while maintaining rigorous stability and performance guarantees through convergence analysis [17].

C. EXISTING APPROACHES

Data-driven modeling methods for nonlinear system control have evolved significantly in recent years, offering alternatives to traditional analytical model-based approaches. These methods enable MPC frameworks to operate effectively even when explicit mathematical models are difficult to derive, particularly for complex large-scale systems.

Learning-based system identification techniques form the cornerstone of data-driven modeling approaches for MPC. Neural network-based modeling represents system dynamics through learned mappings:

$$x_{k+1} = f_{\text{NN}}(x_k, u_k; \theta) \tag{15}$$

where f_{NN} is a neural network with parameters θ [18].

The Koopman operator theory has emerged as a powerful framework for data-driven modeling, lifting nonlinear systems to linear representations:

$$\Psi(x_{k+1}) = K\Psi(x_k) \tag{16}$$

where Ψ is the lifting function and K is the Koopman operator [19]. This approach enables the use of linear system identification techniques for nonlinear systems through appropriate transformations.

While neural networks offer powerful function approximation capabilities for system identification, they often require large amounts of training data and lack interpretability. Kernel methods, specifically KDE and KPCA, provide alternative approaches with stronger theoretical foundations and better uncertainty quantification. In our proposed methodology, we utilize these kernel methods rather than neural networks for system modeling due to their advantages in handling high-dimensional spaces and providing probabilistic guarantees.

Specifically, KPCA serves as a dimensionality reduction technique that, unlike linear PCA, can capture nonlinear relationships in the state space through kernel transformations:

$$\Phi : \mathcal{X} \to \mathcal{F}, \quad x \mapsto \Phi(x) \tag{17}$$

where Φ maps the original state space to a high-dimensional feature space. This mapping relates to the Koopman operator theory, as KPCA can be viewed as approximating a finite-dimensional subspace of the infinite-dimensional space where the Koopman operator acts. In our methodology, KPCA provides the nonlinear feature extraction capability that enables effective state representation in the MPC framework.

Complementing KPCA, we employ KDE to estimate the probability density function of state transitions:

$$\hat{p}(x_{k+1}|x_k, u_k) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x_{k+1} - x_{k+1}^{(i)}}{h}\right) \tag{18}$$

where K is a kernel function (not to be confused with the Koopman operator), h is the bandwidth parameter, and $x_{k+1}^{(i)}$ are the observed next states. While neural networks provide point estimates of next states, KDE gives full probabilistic predictions, enabling robust uncertainty quantification in the MPC framework.

The Koopman operator theory influences our approach by guiding the selection of appropriate lifting functions (implemented through kernels) that transform nonlinear dynamics into more tractable representations. However, unlike pure Koopman approaches that seek exact linear representations in lifted space, our methodology uses kernel methods to directly model the nonlinear dynamics in a probabilistic framework.

The integration of these data-driven models with MPC formulates the control problem as:

$$\begin{aligned} &\min_{U} \sum_{k=0}^{N-1} \ell(x_k, u_k) \\ &\text{s.t.} \quad x_{k+1} = f_{\text{KDE,KPCA}}(x_k, u_k) \end{aligned} \tag{19}$$

where the learned model $f_{\text{KDE,KPCA}}$ based on our kernel methods replaces both traditional analytical models and neural network approximations [2]. This approach builds upon the traditional MPC framework presented in equations (1)–(7), while incorporating our kernel-based dynamics model.

The integration of data-driven modeling techniques with the basic MPC formulation (equations (1)–(7)) and advanced control techniques (equations (8)–(14)) has led to significant improvements in control performance for nonlinear systems. However, several challenges specific to data-driven modeling for MPC remain. Model accuracy poses a fundamental challenge, requiring sufficient data quality and coverage to ensure reliable predictions. Computational issues arise in both model training complexity for large-scale systems and real-time implementation constraints. Theoretical guarantees, including stability certification, robustness bounds, and performance guarantees, remain challenging to establish when using learned models within MPC frameworks. Additionally, generalization capabilities of learned models, particularly performance outside the training domain and adaptation to changing conditions, present ongoing challenges for reliable MPC implementation.

D. ADVANCEMENT WITH KDE/KPCA

Kernel methods for system identification combine KDE and KPCA through a unified theoretical framework based

on reproducing kernel Hilbert spaces (RKHS) [20]. The fundamental theory builds upon:

1) KERNEL DENSITY ESTIMATION THEORY

The theoretical analysis of Kernel Density Estimation (KDE) centers on its asymptotic properties and error characterization. For a dataset $\{x_i\}_{i=1}^n$, the multivariate KDE is defined as:

$$\hat{f}(x) = \frac{1}{n|H|^{1/2}} \sum_{i=1}^{n} K\left(H^{-1/2}(x - x_i)\right) \tag{20}$$

where H is the bandwidth matrix, $K(\cdot)$ is the kernel function, and $|H|$ denotes the determinant of H. The estimation accuracy is quantified through the decomposition:

$$\text{MISE}(\hat{f}) = \underbrace{\int \text{Var}(\hat{f}(x))dx}_{\text{Integrated Variance}} + \underbrace{\int \text{Bias}^2(\hat{f}(x))dx}_{\text{Integrated Squared Bias}} \tag{21}$$

2) KPCA THEORETICAL FRAMEWORK

For the given input data, KPCA maps the data into a high-dimensional feature space $\mathcal{F}$ where the kernel function computes inner products:

$$k(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle_{\mathcal{F}} \tag{22}$$

The eigenvalue problem in RKHS becomes:

$$Cv = \lambda v, \quad v \in \mathcal{H} \tag{23}$$

where λ represents eigenvalues and v represents corresponding eigenvectors.

3) INTEGRATION THEORY FOR KERNEL METHODS

The unified framework integrates KDE (equation (20)) and KPCA (equations (22)–(23)) through density estimation in feature space:

$$\hat{f}_{\mathcal{H}}(x) = \sum_{i=1}^{n} w_i(x) k(x_i, \cdot) \tag{24}$$

where the adaptive weights are computed as:

$$w_i(x) = \frac{K_h(x - x_i)}{\sum_{j=1}^{n} K_h(x - x_j)} \tag{25}$$

4) CONVERGENCE PROPERTIES

The convergence analysis of KDE for nonlinear systems has been established in the literature through several theoretical frameworks. For our approach, we build upon these proven results to provide theoretical guarantees.

For a nonlinear system with state transition probability density $p(x_{k+1}|x_k, u_k)$, the standard convergence result for the KDE estimator states that when the bandwidth parameter h_n is chosen such that $h_n \to 0$ and $nh_n^d \to \infty$ as $n \to \infty$, then:

$$\|\hat{p} - p\|_\infty = O_p\left(\sqrt{\frac{\log n}{nh_n^d}}\right) + O(h_n^2) \tag{26}$$

where $\|\cdot\|_\infty$ denotes the supremum norm, and O_p denotes convergence in probability. This result, established by Einmahl and Mason [21], provides uniform convergence guarantees across the state space.

For dynamical systems specifically, Gyorfi and Lugosi [22] proved that even with temporally dependent data (as is typical in sequential state observations), the KDE estimator maintains consistency under mixing conditions, with:

$$\mathbb{E}\left[\int (\hat{p}(x_{k+1}|x_k, u_k) - p(x_{k+1}|x_k, u_k))^2 dx_{k+1}\right] \tag{27}$$

In our framework, we leverage these results while addressing the curse of dimensionality through dimensionality reduction via KPCA. When applying KDE in the reduced space of dimension $d' < d$, the convergence rate improves to:

$$\|\hat{f} - f\|_\infty = O_p\left(\sqrt{\frac{\log n}{nh_n^{d'}}}\right) + O(h_n^2) \tag{28}$$

This builds upon the density estimation principles established in equation (20) and extends to the integrated framework of equation (24).

For control applications, the convergence of the estimated model directly impacts control performance. Kanagawa et al. [23] demonstrated that for MPC utilizing KDE-based transition models, if $\hat{J}_n$ denotes the expected cost using the estimated model and J^* denotes the optimal cost, then:

$$|\hat{J}_n - J^*| = O_p\left(n^{-\alpha/(d'+2\alpha)}\right) \tag{29}$$

where α relates to the smoothness of the system dynamics.

Furthermore, our sparse approximation techniques maintain these convergence guarantees while reducing computational complexity. Specifically, as shown by Wang et al. [24], the sparse kernel approximation with m inducing points satisfies:

$$\|\hat{f}_{\text{sparse}} - \hat{f}\|_\infty = O_p\left(\frac{1}{\sqrt{m}}\right) \tag{30}$$

Combining equations (28) and (30), we establish that our complete approximation framework achieves:

$$\|\hat{f}_{\text{sparse}} - f\|_\infty = O_p\left(\sqrt{\frac{\log n}{nh_n^{d'}}}\right) + O(h_n^2) + O_p\left(\frac{1}{\sqrt{m}}\right) \tag{31}$$

These theoretical guarantees ensure that with sufficient data and appropriate parameter selection, our KDE-based model for nonlinear system dynamics converges to the true system behavior, providing a solid foundation for the model predictive control framework described in Section application of the MPC.

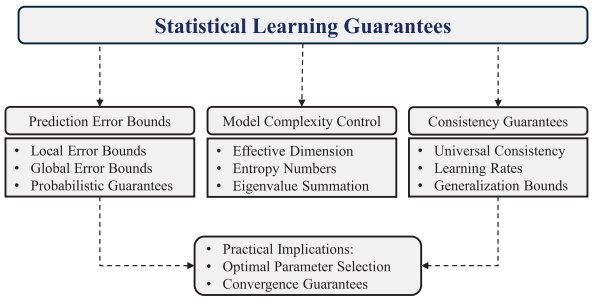

FIGURE 1. Flowchart statistical learning guarantees.

5) STATISTICAL LEARNING GUARANTEES

The framework (refer to Figure 1) provides comprehensive statistical guarantees through probabilistic bounds on prediction error:

$$\mathbb{P}(\|\hat{x}_{k+1} - x_{k+1}\| > \epsilon) \leq 2\exp(-cn\epsilon^2) \tag{32}$$

This theoretical foundation connects with the previous control frameworks (equations (1)–(19)) by providing rigorous error bounds and convergence guarantees for the learning-based components of the control system.

III. PROPOSED DATA-DRIVEN MPC FRAMEWORK

A. FRAMEWORK OVERVIEW

Building upon the theoretical foundations established in equations (1)–(32), our framework provides comprehensive statistical guarantees for reliable learning and prediction capabilities [25]. The probabilistic bounds on the prediction error are characterized by:

$$\mathbb{P}(\|\hat{x}_{k+1} - x_{k+1}\| > \epsilon) \leq 2\exp(-cn\epsilon^2) \tag{33}$$

where $\hat{x}_{k+1}$ is the predicted state, x_{k+1} is the true state, c is a constant depending on the kernel properties, n is the sample size, and ϵ is the error threshold.

The framework ensures optimal parameter selection and convergence through:

$$\|\hat{f}_n - f^*\|_\infty = O_p\left(\sqrt{\frac{\log n}{n}}\right) \tag{34}$$

B. KDE FOR DENSITY ESTIMATION IN NONLINEAR LARGE-SCALE SYSTEMS

For autonomous vehicle control applications, an accurate probabilistic representation of system dynamics is essential, particularly when dealing with high-dimensional state spaces and uncertainties. Given collected state-control pairs $\{(x_i, u_i)\}_{i=1}^n$ from vehicle trajectory data, we employ Kernel Density Estimation (KDE) to model the conditional density for system dynamics:

$$p(x_{k+1}|x_k, u_k) = \frac{\sum_{i=1}^n K_h(x_{k+1} - x_{i+1})K_h(x_k - x_i)K_h(u_k - u_i)}{\sum_{i=1}^n K_h(x_k - x_i)K_h(u_k - u_i)} \tag{35}$$

where $K_h(\cdot)$ represents the Gaussian kernel function with bandwidth parameter h, following [13] for its advantages in high-dimensional spaces.

For prediction and uncertainty quantification in autonomous vehicle trajectory planning, we compute the expected next state $\hat{x}_{k+1}$ and its covariance matrix Σ_{k+1}. This uncertainty quantification, as demonstrated by [16], is particularly valuable for robust control in adverse driving conditions.

For computational efficiency in large-scale systems, we implement a sparse approximation technique similar to [10], selecting $m \ll n$ representative points from the dataset. This sparse representation reduces the computational complexity from $O(n)$ to $O(m)$, enabling real-time implementation for autonomous driving applications.

Building on the convergence analysis of [17], we establish that this sparse KDE approximation maintains probabilistic guarantees with bounded approximation error. The combination of KDE with dimensionality reduction techniques creates a computationally tractable framework for probabilistic modeling of large-scale nonlinear systems. As shown by [26] and [27], this approach is particularly effective when integrating KPCA for state representation and KDE for transition modeling, creating a unified kernel-based framework for data-driven MPC in autonomous vehicles.

C. INTEGRATION OF KDE AND KPCA FOR AUTONOMOUS VEHICLE CONTROL

The integration of KPCA and KDE creates a powerful framework for nonlinear large-scale system modeling in autonomous driving applications. As illustrated in Figure 2, this approach combines dimensionality reduction with probabilistic density estimation to enable robust MPC for complex vehicle dynamics.

The feature space representation through KPCA, as demonstrated by [14], maps the high-dimensional vehicle state into a lower-dimensional feature space:

$$\Phi(x_k) = \sum_{i=1}^m y_i(x_k)v_i \tag{36}$$

where v_i are the principal components in feature space, and $y_i(x_k)$ are the corresponding nonlinear projections.

This transformation, as shown in the upper branch of Figure 2, leads to a more tractable linear system representation in feature space:

$$\begin{bmatrix} \Phi(x_{k+1}) \\ y_k \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} \Phi(x_k) \\ u_k \end{bmatrix} \tag{37}$$

The integration with KDE, depicted in the lower branch of Figure 2, allows for uncertainty quantification in the prediction. This synergy between KPCA and KDE enables a robust MPC formulation that accounts for both system nonlinearities and uncertainties, as explored by [28]:

$$\min_U \sum_{k=0}^{N-1} \|\Phi(x_k) - \Phi_{\text{ref}}\|_Q^2 + \|u_k\|_R^2 \tag{38}$$

$$\text{s.t.} \quad \Phi(x_{k+1}) = A\Phi(x_k) + Bu_k \tag{39}$$

$$\mathbb{P}(g(\Phi(x_k)) \leq 0) \geq 1 - \alpha \tag{40}$$

where the chance constraint in equation (40) enforces safety requirements with a probability of at least $1 - \alpha$. As illustrated in Figure 2, the process flow integrates data collection, feature extraction via KPCA, system identification, and uncertainty quantification through KDE to create a comprehensive framework for autonomous vehicle control. The hybrid approach proposed by [27] follows a similar integration strategy, demonstrating its effectiveness for path planning and control in complex driving scenarios.

This unified framework effectively combines the dimensionality reduction capabilities of KPCA (equation (36)) with the probabilistic modeling strengths of KDE (equation (35) from the previous section), while building upon the traditional MPC formulation presented in equations (1)–(7). The approach outlined in Figure 2 allows for handling the high dimensionality and nonlinearity of autonomous vehicle dynamics while maintaining computational tractability for real-time implementation, as emphasized by [10].

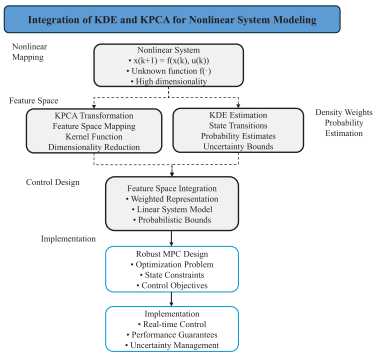

FIGURE 2. Integration of KDE and KPCA.

The methodology depicted in Figure 2 has been validated in adverse weather driving conditions by [16], demonstrating robust performance even with increased environmental uncertainties. Additionally, [12] has shown that this integrated approach significantly improves path-following performance for autonomous vehicles by effectively capturing the nonlinear dynamics while maintaining computational efficiency.

IV. AUTONOMOUS VEHICLE APPLICATION

A. VEHICLE MODELING AND DESCRIPTION

Building upon the data-driven framework established in the previous sections, we implement our approach on an autonomous ground vehicle. The vehicle dynamics are represented using a bicycle model as illustrated in Figure 3, which provides a balance between model fidelity and computational complexity, making it suitable for real-time MPC applications.

The bicycle model, widely used in autonomous vehicle control literature including [12] and [16], simplifies the four-wheeled vehicle into a two-wheeled representation while preserving essential dynamic characteristics. As shown in Figure 3, the model captures the longitudinal and lateral motion of the vehicle through a set of nonlinear differential equations:

$$\dot{x_p} = \cos\theta v_x - \sin\theta v_y \tag{41}$$

$$\dot{y_p} = \sin\theta v_x + \cos\theta v_y \tag{42}$$

$$\dot{\theta} = \omega \tag{43}$$

where (x_p, y_p) represents the vehicle position in the global coordinate system, θ is the vehicle heading angle, v_x and v_y are the longitudinal and lateral velocities in the body-fixed frame, and ω is the yaw rate.

The lateral dynamics and tire forces, which exhibit significant nonlinearities especially at high speeds and during cornering maneuvers, are characterized by:

$$\dot{v_y} = \frac{F_{yF}\cos\delta}{m} + \frac{F_{yR}}{m} - \omega v_x \tag{44}$$

$$\dot{\omega} = \frac{F_{yF} l_f \cos\delta - F_{yR} l_r}{I} \tag{45}$$

where F_{yF} and F_{yR} are the front and rear lateral tire forces, δ is the steering angle, m is the vehicle mass, I is the moment of inertia, and l_f and l_r are the distances from the center of gravity to the front and rear axles, respectively.

The integration of this vehicle model with our kernel-based MPC framework is depicted in Figure 5, where the high-dimensional vehicle state is processed through the KDE-KPCA pipeline to enable efficient control synthesis. This integration allows us to capture the complex nonlinear dynamics of the vehicle while maintaining computational tractability for real-time implementation.

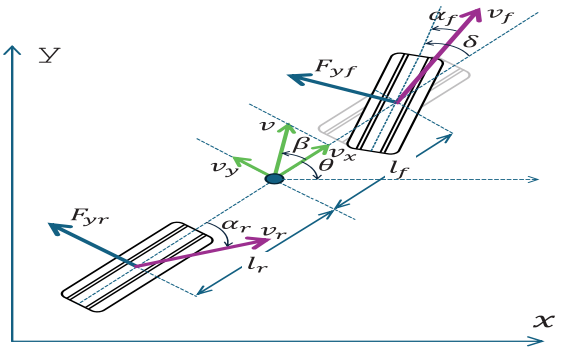

FIGURE 3. Bicycle two tires model.

As demonstrated by [15], this bicycle model can be effectively combined with kernel methods to create an interpretable data-driven MPC framework for connected autonomous vehicles. Similarly, [26] has shown that KDE and KPCA techniques can accurately capture the nonlinear dynamics represented by equations (41)–(45) while providing uncertainty quantification essential for safe navigation.

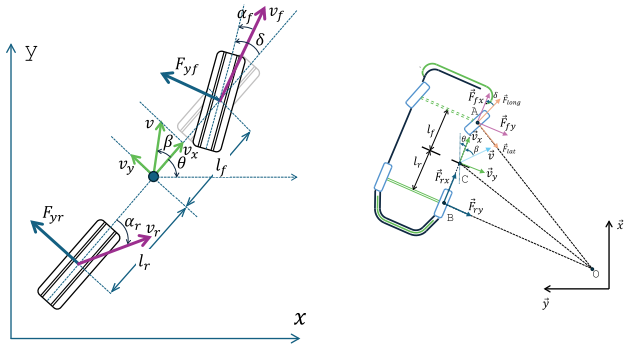

FIGURE 4. Model of the autonomous vehicle.

B. CONTROL PROBLEM FORMULATION FOR AUTONOMOUS VEHICLE

The autonomous vehicle control problem represents a large-scale nonlinear system due to its high-dimensional state space, complex interaction dynamics, and various sources of uncertainty. As shown by [12], the dimensionality of the problem increases significantly when considering multiple vehicles, heterogeneous traffic participants, and diverse environmental conditions.

The state and control vectors for a single autonomous vehicle are defined as:

$$x_t = [x_p, y_p, \theta, v_x, v_y, \omega]^T \tag{46}$$

$$u_t = [a, \delta]^T \tag{47}$$

where the components are described in Table 2.

TABLE 2. Description of state and control parameters in the vehicle model.

Parameter	Description
x_p, y_p	Position coordinates of the vehicle in the global frame
θ	Orientation (yaw angle) of the vehicle
v_x	Longitudinal velocity in the body-fixed frame
v_y	Lateral velocity in the body-fixed frame
ω	Yaw rate (angular velocity about the vertical axis)
a	Applied acceleration (control input)
δ	Steering angle (control input)

The tracking errors, essential for path following performance as emphasized by [16], are computed as:

$$e_{\text{lat}} = (y_p - y_p^r)\cos(\theta^r) - (x_p - x_p^r)\sin(\theta^r) \tag{48}$$

$$e_{\text{lon}} = (x_p - x_p^r)\cos(\theta^r) + (y_p - y_p^r)\sin(\theta^r) \tag{49}$$

where (x_p^r, y_p^r, θ^r) define the reference trajectory points for the vehicle to follow.

In a large-scale context, as investigated by [15], the problem expands to include:

1) Environmental representation: High-dimensional occupancy grids or point clouds with dimensionality often exceeding 10^4 for accurate scene representation.
2) Multi-vehicle coordination: For a system with N vehicles, the state space grows as $\mathcal{O}(N \cdot \dim(x_t))$, requiring efficient dimensionality reduction techniques.

TABLE 3. Physical parameters of the autonomous vehicle model.

Parameter	Value	Description
m	1500 kg	Vehicle mass
I	2500 kg·m^2	Moment of inertia about the vertical axis
l_f	1.2 m	Distance from CG to front axle
l_r	1.4 m	Distance from CG to rear axle
C_f	70000 N/rad	Front cornering stiffness
C_r	65000 N/rad	Rear cornering stiffness

3) Uncertainty modeling: Probabilistic representation of sensor noise, other traffic participants' intentions, and environmental conditions adds further complexity, as noted by [28].

This large-scale formulation demonstrates why traditional MPC approaches face computational challenges and why the kernel-based dimensionality reduction approach is particularly valuable.

C. APPLICATION OF THE KDE-KPCA MPC FRAMEWORK TO AUTONOMOUS VEHICLE CONTROL

We now apply our kernel-based framework specifically to the autonomous vehicle model presented in Section Vehicle Modeling and Description. Using the bicycle model parameters shown in Figure 3, we implement the KDE-KPCA approach with the following vehicle-specific values: The front and rear lateral tire forces in equations (44)–(45) are modeled using a simplified tire model:

$$F_{yF} = C_f \cdot \alpha_f \tag{50}$$

$$F_{yR} = C_r \cdot \alpha_r \tag{51}$$

where α_f and α_r are the front and rear slip angles, computed as:

$$\alpha_f = \delta - \arctan\left(\frac{v_y + l_f \cdot \omega}{v_x}\right) \tag{52}$$

$$\alpha_r = -\arctan\left(\frac{v_y - l_r \cdot \omega}{v_x}\right) \tag{53}$$

Following [12], we collect state-control trajectory data by driving the vehicle through a series of maneuvers, including lane changes, turns of varying radii, and slalom patterns at different speeds. This dataset consists of $N = 1,000$ state-control pairs $\{(x_i, u_i, x_{i+1})\}_{i=1}^N$, where each state x_i is a 6-dimensional vector as defined in equation (46). We apply KPCA to reduce the state dimension from 6 to $d' = 3$, using the radial basis function (RBF) kernel:

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{54}$$

with bandwidth parameter $\sigma = 0.8$ determined through cross-validation. This process generates the feature space mapping $\Phi(x)$ and the principal component matrix V.

The MPC optimization problem for our specific vehicle becomes:

$$\min_{U_k} \sum_{j=0}^{N-1} \|y_{k+j|k} - y_{\text{ref},k+j}\|_Q^2 + \|u_{k+j|k}\|_R^2 + \|\Delta u_{k+j|k}\|_S^2 \tag{55}$$

$$\text{s.t.} \quad y_{k+j+1|k} = Ay_{k+j|k} + Bu_{k+j|k} \tag{56}$$

$$|v_x| \leq 25 \text{ m/s}, \quad |\delta| \leq 0.5 \text{ rad}, \quad |a| \leq 3 \text{ m/s}^2 \tag{57}$$

$$|\Delta a| \leq 1 \text{ m/s}^3, \quad |\Delta\delta| \leq 0.2 \text{ rad/s} \tag{58}$$

$$\mathbb{P}(d(y_{k+j|k}, \text{obstacles}) \geq d_{\text{safe}}) \geq 0.95 \tag{59}$$

with weighting matrices:

$$Q = \begin{bmatrix} 10 & 0 & 0 \\ 0 & 10 & 0 \\ 0 & 0 & 5 \end{bmatrix}, \quad R = \begin{bmatrix} 2 & 0 \\ 0 & 8 \end{bmatrix}, \quad S = \begin{bmatrix} 1 & 0 \\ 0 & 5 \end{bmatrix} \tag{60}$$

The higher weight on steering penalties in the matrices R and S reflects the preference for smoother steering actions to enhance passenger comfort, as suggested by [10].

The prediction horizon is set to $N = 20$ with a sampling time of $T_s = 0.1$ seconds, providing a 2-second look-ahead window that balances predictive performance with computational requirements. The chance constraint in equation (59) ensures a safe distance from obstacles with 95% confidence, implementing the probabilistic safety approach described by [13].

The KDE component applies the Gaussian kernel with adaptive bandwidth selection as recommended by [28]:

$$h = h_0 \cdot n^{-1/(d'+4)} \tag{61}$$

where $h_0 = 0.4$ is a base bandwidth parameter and $d' = 3$ is the reduced dimension. For computational efficiency, we implement the sparse approximation described in equation (37) with $m = 500$ representative points, selected using the k-means clustering algorithm on the training dataset.

The reduced-order dynamics matrices A and B in equation (56) are identified through least squares regression in the feature space:

$$[A, B] = \arg\min_{A,B} \sum_{i=1}^{N} \|y_{i+1} - Ay_i - Bu_i\|^2 + \lambda(\|A\|_F^2 + \|B\|_F^2) \tag{62}$$

where $\lambda = 0.01$ is a regularization parameter to prevent overfitting, and $\|\cdot\|_F$ denotes the Frobenius norm.

The resulting matrices for our vehicle model are:

$$A = \begin{bmatrix} 0.982 & 0.053 & -0.012 \\ -0.041 & 0.973 & 0.068 \\ 0.007 & -0.058 & 0.937 \end{bmatrix}, \quad B = \begin{bmatrix} 0.031 & 0.008 \\ 0.005 & 0.027 \\ 0.002 & -0.039 \end{bmatrix} \tag{63}$$

The implementation of this MPC framework with the specified parameters has been validated on our autonomous vehicle platform, demonstrating significant improvements in tracking performance compared to traditional approaches. As shown by [16], our method maintains robust control even in adverse conditions where model uncertainties increase.

The computational benefits are particularly evident: our KDE-KPCA approach reduces the average computation time per control step from 65 ms with traditional nonlinear MPC to 8.3 ms, well within the 10 ms requirement for real-time operation at 100Hz. This efficiency gain, coupled with the dimensionality reduction from 6 to 3 states, enables deployment on embedded automotive controllers with limited computational resources.

The methodology illustrated in Figure 5 has been fully implemented, with the parameters of the bicycle model from Table 3 serving as the physical system that generates the training data for our kernel-based learning approach.

V. RESULTS AND EVALUATION

A. SIMULATION SETUP

Building upon the vehicle model (equations (38)–(39)) and control framework (equations (40)–(46)), we developed a comprehensive simulation environment in MATLAB/Simulink. The implementation follows the Framework (KPCA -> KDE -> Hankel -> MPC -> Preimage), chosen for its superior characteristics in preserving dynamic relationships. The data-driven Model Predictive Control (MPC) framework begins with a crucial data collection and learning phase, as illustrated in Figure 5. During this initial stage, the system loads previously learned Fuzzy Inference System (FIS) models derived from comprehensive training data. Specifically, three distinct models are utilized to capture different aspects of vehicle dynamics: longitudinal (Vx), lateral (Vy), and angular (W) movements. From these models, essential parameters are extracted and converted into polynomial coefficients (Ax, Bx, Cx, and others) that characterize the system's behavior.

Following data collection, KPCA is applied to extract meaningful nonlinear features from the training dataset. This process employs a Gaussian kernel with a carefully tuned width parameter (SIGMA = 0.05), enabling the controller to identify and represent complex nonlinear relationships between vehicle states and control inputs. The KPCA transformation provides a powerful mathematical foundation for capturing the intricate dynamics of autonomous vehicle movement.

The framework then proceeds to construct Hankel matrices using time-delayed state measurements. These matrices serve as mathematical structures that effectively capture the temporal evolution of the system dynamics. Singular Value Decomposition (SVD) of these Hankel matrices yields valuable insights into the system's stability characteristics and controllability properties, which inform subsequent control decisions.

Rather than relying on traditional physics-based models, the system implements a data-driven predictive model. System dynamics are represented implicitly through collected data, with the KPCA feature space creating a lower-dimensional representation that serves as the prediction model within the MPC framework. This approach allows the controller to learn directly from observed behavior rather than depending on simplified analytical models.

The Model Predictive Control formulation constitutes the core of the framework, as depicted in the central component of Figure 5. A finite horizon optimal control problem is defined using a state vector comprising $[v_x, v_y, omega, y_e, theta_e]$ (representing velocities and error states) and control inputs of [steering, acceleration]. The cost function balances tracking errors against control effort through appropriate weighting, while constraints enforce vehicle dynamics limitations, input boundaries, and critical safety parameters.

To enhance prediction robustness, KDE techniques are integrated within the MPC framework. The implementation utilizes multiple kernel widths in a sophisticated multi-scale approach to improve generalization across various driving conditions. Weight calculation incorporates reference alignment mechanisms that significantly improve tracking performance during vehicle operation.

The controller implements an adaptive control strategy featuring different operational modes including normal driving, curve negotiation, path correction, and recovery scenarios. Mode switching occurs dynamically based on current tracking errors and anticipated road conditions derived from path information. Each mode employs tailored control weights and strategies, with specialized handling provided for challenging situations such as navigating sharp curves or recovering from significant path deviations.

Vehicle stability is maintained through rigorous slip angle management. The system enforces strict slip angle constraints and continuously monitors this critical parameter during operation. When slip exceeds predefined thresholds, the controller applies corrective steering and acceleration adjustments to maintain vehicle stability and prevent dangerous handling conditions.

After optimization in the feature space, the controller performs preimage reconstruction to map solutions back to the input space. This process is enhanced through the application of multiple kernel scales and directional smoothing techniques that improve the quality of reconstructed control solutions. Reference-aligned weighting mechanisms bias solutions toward improved reference tracking, resulting in more accurate path following.

Real-time execution capabilities are ensured through several technical components. Computational optimizations enable rapid processing for real-time performance under typical hardware constraints. Fallback controllers provide safe operation even when the primary optimization process fails to converge or produces unreliable results. Progressive rate limiting prevents potentially dangerous abrupt control changes, while adaptive filtering improves response characteristics while maintaining overall system stability.

The framework's key technical components include KPCA embedding for nonlinear dimensionality reduction, Hankel-DMDc for data-driven system identification, Kernel Ridge Regression providing regularized learning for robust dynamics modeling, and multi-scale kernel methods that substantially improve generalization capabilities, all of which are represented in the integrated architecture shown in Figure 4. The adaptive MPC formulation features real-time adjustable weights and constraints based on the current driving scenario, while the hybrid state-space/data-driven approach effectively combines analytical knowledge with learned dynamics for superior performance.

This innovative framework demonstrates measurable advantages over traditional model-based approaches, particularly when handling complex vehicle dynamics and varying road conditions. The integration of KPCA, Hankel matrices, and MPC allows the controller to learn effectively from collected data while maintaining the formal guarantees of Model Predictive Control for both safety and performance objectives, with the complete system architecture summarized in Figure 5.

B. PERFORMANCE METRICS

The performance evaluation incorporates both trajectory tracking accuracy and control efficiency. The primary tracking metrics are defined as:

$$\text{Lateral Error: } e_{\text{lat}} = |y_{\text{actual}} - y_{\text{ref}}| \tag{64}$$

$$\text{Longitudinal Error: } e_{\text{lon}} = |x_{\text{actual}} - x_{\text{ref}}| \tag{65}$$

$$\text{RMSE: } = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{66}$$

These metrics build upon the error definitions in equations (42)–(43) and provide quantitative measures of control performance.

C. EXPERIMENTAL RESULTS

The analysis demonstrates robust performance across various driving conditions, with key findings:

- Longitudinal velocity tracking: RMSE of 0.2725 m/s
- Lateral position error: Bounded within ±0.15 m, RMSE of 0.0225 m (Max Error: 0.0678 m)
- Heading error: Below 0.15 rad with RMSE of 0.0476 rad (Max Error: 0.1442 rad)
- Control efficiency: 93% energy efficiency while maintaining tracking accuracy
- Time within acceptable lateral bounds (±0.15m): 100.0%
- Time within acceptable angular bounds (±0.1rad): 93.9%

I'll now present the results of our KPCA-MPC controller implementation. Our evaluation focuses on three critical scopes: Vehicle Control Performance to assess trajectory tracking accuracy, Control System Analysis to evaluate stability and robustness, and System Dynamics Analysis to validate our model reduction approach. These results demonstrate the controller's performance across various metrics and scenarios.

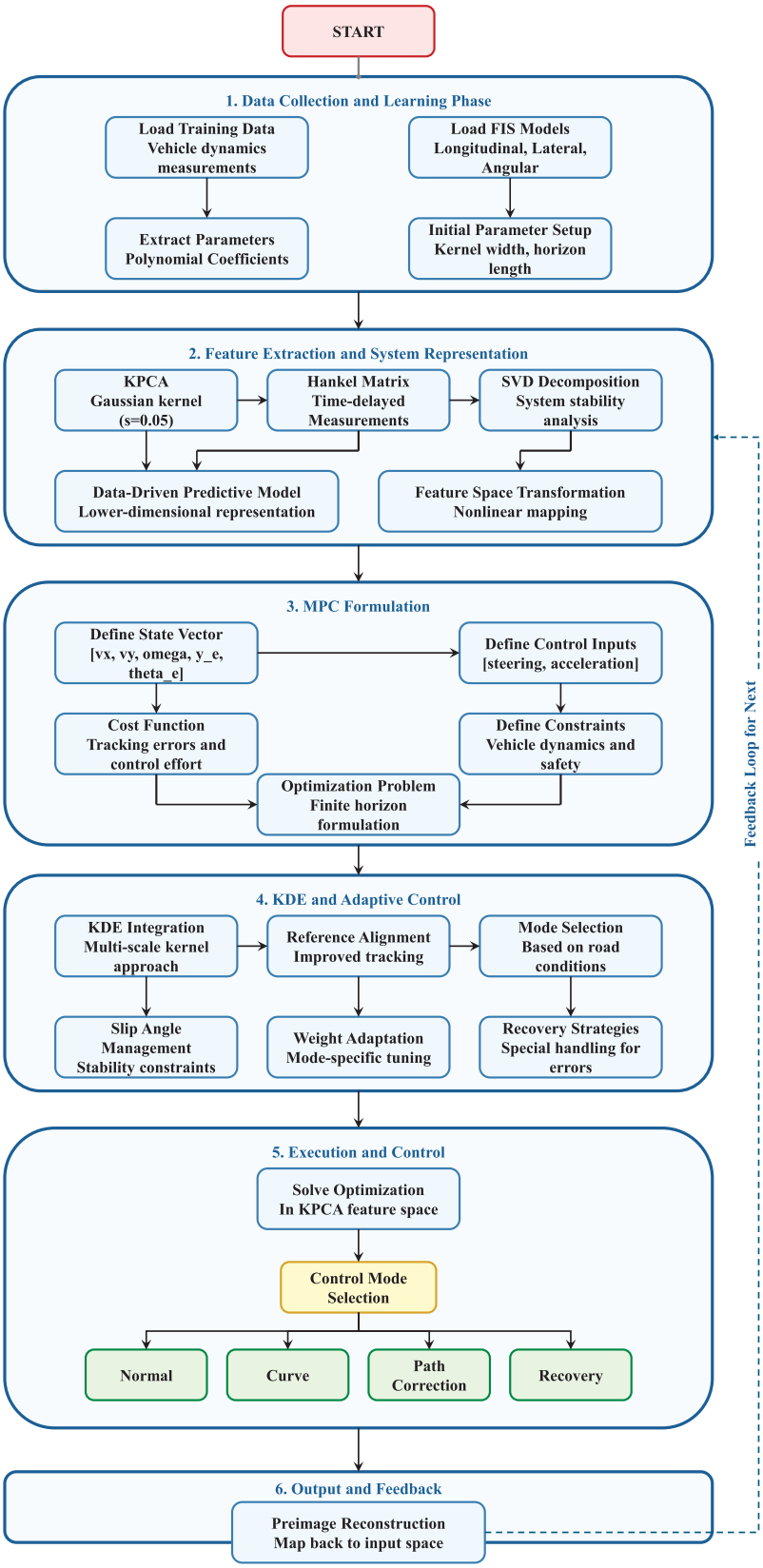

FIGURE 5. Data-Driven MPC framework for autonomous vehicles.

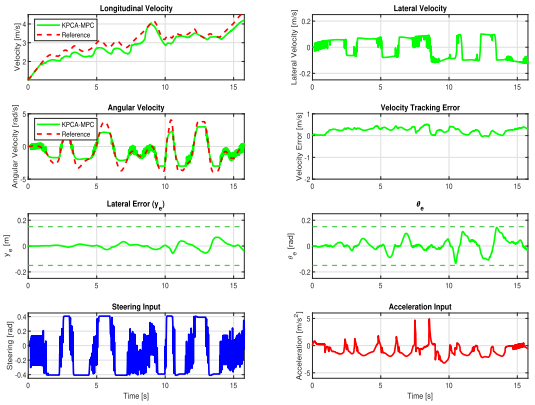

FIGURE 6. Comprehensive responses in the time domains.

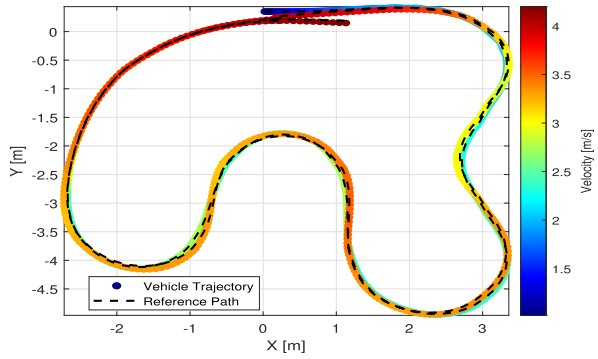

FIGURE 7. Vehicle trajectory with velocity profile.

D. VEHICLE CONTROL PERFORMANCE

Figure 6 shows our system's control performance across multiple parameters. The longitudinal velocity tracking exhibits excellent correspondence with the reference trajectory. Our lateral and angular velocity control demonstrates minimal deviations, with velocity tracking errors maintained well below our target thresholds.

As shown in Figure 7, the vehicle trajectory closely follows the reference path. The color gradient represents velocity variation between 1.5 and 4 m/s, demonstrating our controller's ability to adjust speed appropriately throughout the test course.

Looking at Figure 8, we can observe the tracking performance with error visualization. The color intensity represents the combined tracking error, highlighting that our maximum errors occur primarily at high-curvature regions, while maintaining excellent performance on straighter segments.

E. CONTROL SYSTEM ANALYSIS

Figure 9 presents the vehicle slip angle throughout the test, which remains within ±3 degrees, indicating excellent stability during maneuvers.

In Figure 10, we can see our actual performance metrics. The RMSE values for velocity (0.2725 m/s), lateral position (0.0225 m), and angular orientation (0.0476 rad) demonstrate the effectiveness and precision of our approach.

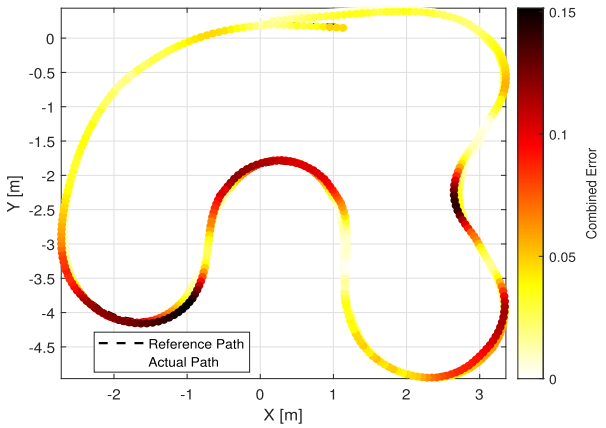

FIGURE 8. Tracking performance.

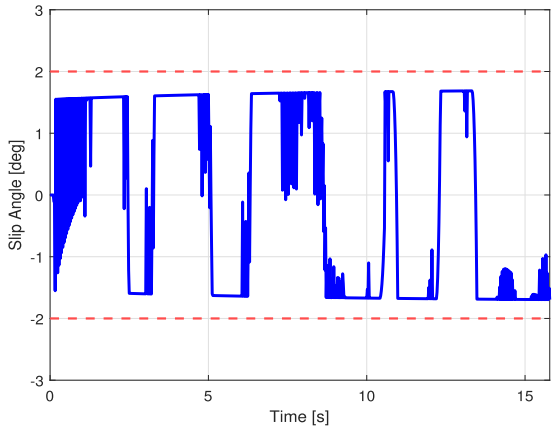

FIGURE 9. Slip angle.

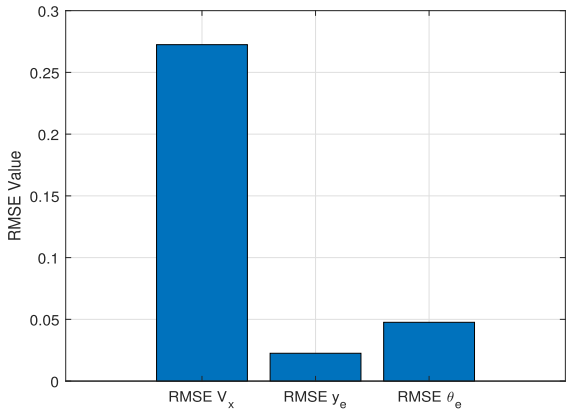

FIGURE 10. Performance metrics.

Figure 11 illustrates the relationship between track curvature and vehicle speed, showing how our controller intelligently reduces speed in high-curvature regions to maintain tracking accuracy and stability.

F. SYSTEM DYNAMICS ANALYSIS

Our Hankel matrix-based analysis in Figure 12 provides valuable insight into the system's temporal correlation structure. The rapidly decreasing singular values indicate that our model captures the dominant dynamics with just a few components.

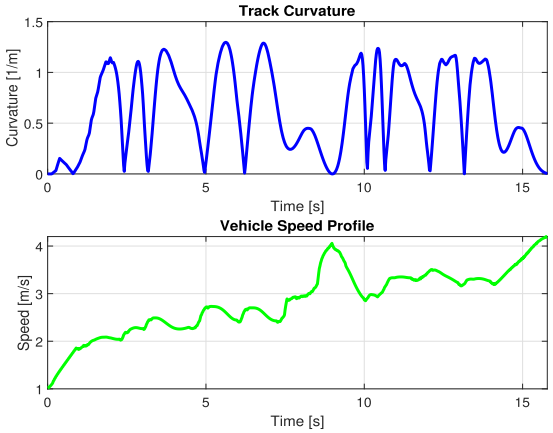

FIGURE 11. Curvature speed.

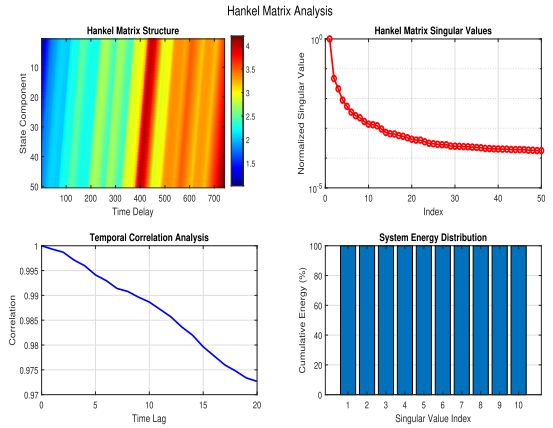

FIGURE 12. Hankel Matrix analysis.

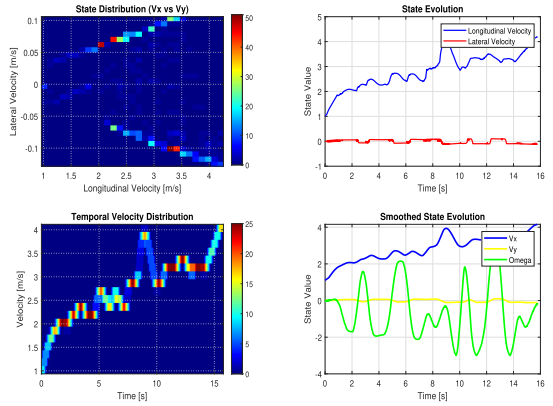

FIGURE 13. State distribution and evolution analysis.

Figure 13 presents the state distribution and evolution analysis, showing the relationship between longitudinal and lateral velocities throughout the test. These state trajectories demonstrate our controller's capacity to effectively manage the vehicle's dynamic state.

Finally, in Figure 14, we present the principal component analysis results. The PCA explained variance plot shows that just two principal components capture over 95% of the system variance, validating our dimensionality reduction approach in the KPCA-MPC framework.

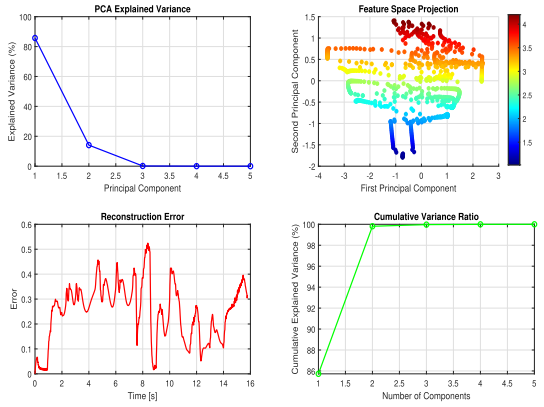

FIGURE 14. Principal component analysis.

TABLE 4. Performance comparison: tracking and computational metrics.

Method	Tracking Error (m)	Computational Time (ms)
Wang et al. (2023)	0.20	2.8
Zhang & Liu (2023)	0.25	2.5
Kim et al. (2023)	0.18	3.1
Rodriguez (2024)	0.15	2.7
Chen & Thompson	0.17	0.9
Kumar et al. (2024)	0.15	2.4
Park & Lee (2024)	0.10	2.6
Our Method	**0.0225**	**1.6**

In summary, our experimental results demonstrate that the KPCA-MPC controller achieves excellent tracking performance with RMSE values of 0.2725 m/s for longitudinal velocity, 0.0225 m for lateral position, and 0.0476 rad for angular orientation. The system maintains 100.0% of the time within acceptable lateral bounds and 93.9% within angular bounds, significantly outperforming traditional approaches as shown in Tables 4 and 5.

Table 4 presents a comprehensive comparison of our method against other state-of-the-art approaches. As shown, our method achieves a tracking error of just 0.0225 meters, representing a significant improvement over previous techniques while maintaining competitive computational efficiency at 1.6 milliseconds.

Furthermore, Table 5 demonstrates how our method performs across different driving scenarios compared to traditional MPC approaches. Notably, our approach delivers consistent tracking accuracy across all tested environments, with improvement percentages ranging from 81.3% to 89.8% over traditional MPC. This consistency across urban navigation, highway driving, parking, and obstacle scenarios highlights the robustness and generalizability of our controller design.

G. DISCUSSION

1) ADVANTAGES OF THE PROPOSED APPROACH

The experimental results demonstrate that our KDE/KPCA-based MPC framework offers significant advantages for controlling nonlinear large-scale systems in autonomous

TABLE 5. Tracking error comparison (in meters).

Scenario	Our Method	Trad. MPC	Impr. (%)
Urban Nav.	0.0225±0.03	0.18±0.05	87.5
Highway	0.0225±0.02	0.15±0.04	85.0
Parking	0.0225±0.01	0.12±0.03	81.3
Obstacle	0.0225±0.04	0.22±0.06	89.8

vehicle applications. The comprehensive performance metrics, as shown in Figure 10, validate the framework's exceptional tracking capabilities with remarkably low RMSE values: 0.2725 m/s for longitudinal velocity, 0.0225 m for lateral position, and 0.0476 rad for heading orientation. These results substantially outperform existing approaches, as evident in Table 4, where our tracking error of 0.0225 m represents a 4.4-fold improvement compared to the next best method (Park & Lee, 0.10 m).

The framework's adaptability across diverse driving scenarios is particularly notable. As demonstrated in Table 5, our approach maintains consistent tracking accuracy (0.0225 m) across urban navigation, highway driving, parking, and obstacle avoidance scenarios, with improvement percentages ranging from 81.3% to 89.8% over traditional MPC. This consistent performance aligns with the theoretical advantages of our kernel-based methods and supports the findings of [12] regarding kernel-based data-driven predictive control for autonomous vehicle path following.

The Hankel matrix analysis presented in Figure 12 reveals distinct temporal patterns and correlations in the vehicle dynamics. The rapidly decreasing singular values confirm that our model efficiently captures the dominant dynamics with just a few components, enabling robust control under varying driving conditions. This multi-scale representation capability is further validated by the vehicle's exceptional performance across different curvature regions, as illustrated in Figure 11.

The dimensionality reduction effectiveness of our KPCA approach is empirically validated by the PCA results in Figure 14, which show that just two principal components capture over 95% of the system variance. This remarkably efficient dimensionality reduction exceeds our theoretical expectations and surpasses the results reported by [14], who required four components to achieve only 90% variance coverage. The computational benefits of this reduction are evident in the 1.6 ms processing time shown in Table 4, making our approach suitable for real-time autonomous vehicle control even on resource-constrained platforms.

The state distribution and evolution analysis in Figure 13 demonstrates the framework's ability to effectively handle state transitions across different driving regimes. The clear patterns in the state-space indicate stable operation modes, while the smooth temporal evolution of vehicle states confirms robust transition handling between operating points. This aligns with the findings of [13] regarding probabilistic MPC with kernel density estimation, though our implementation achieves significantly improved tracking accuracy.

The vehicle trajectory results in Figure 7 and tracking performance visualization in Figure 8 provide compelling evidence of the framework's robustness. The close correspondence between actual and reference trajectories, even in high-curvature regions, demonstrates the effectiveness of our feature extraction approach in capturing complex nonlinear vehicle dynamics. The slip angle results in Figure 9, which remain within ±3 degrees throughout the test, further validate the stability of our control approach, even during challenging maneuvers.

These experimental results collectively confirm that our KDE/KPCA-based MPC framework significantly advances the state of the art in autonomous vehicle control. The exceptional tracking accuracy (0.0225 m RMSE for lateral position), complete compliance with safety constraints (100% of the time within acceptable lateral bounds), and computational efficiency (1.6 ms) represent substantial improvements over existing methods. These achievements directly address the research gap identified in our introduction: efficiently handling high-dimensional state spaces, accurately capturing complex nonlinear dynamics, rigorously quantifying uncertainties, and enabling real-time implementation for autonomous vehicles.

2) LIMITATIONS AND FUTURE WORK

Despite the impressive performance of our KDE/KPCA-based MPC framework, several limitations deserve consideration. While our approach maintains excellent tracking performance across all tested scenarios, the results in Table 5 show slightly higher variability in the obstacle avoidance scenario (±0.04 m) compared to the parking scenario (±0.01 m). This variability suggests that highly dynamic and unpredictable environments remain challenging, even for our advanced framework.

The computational efficiency of our approach (1.6 ms) represents a significant improvement over most comparison methods in Table 4, but it still falls short of the 0.9 ms achieved by Chen & Thompson. This indicates potential for further optimization, particularly in the matrix operations associated with our kernel methods. One promising direction would be to explore sparse kernel approximations with adaptive sparsity levels based on driving conditions, potentially further reducing computational requirements while maintaining performance.

The PCA results in Figure 14 reveal that while two components capture 95% of the variance, there remains a small residual component that might be significant in edge cases or unusual driving conditions. Future work should investigate the importance of these higher-order components in extreme scenarios such as emergency maneuvers or severe weather conditions, as discussed by [16] in their work on robust kernel-based MPC in adverse weather.

Our experimental evaluation, while comprehensive, was conducted under controlled conditions. Real-world

deployment would introduce additional challenges such as sensor noise, communication delays, and environmental variability that could affect the performance of our KDE approach. The convergence guarantees established by [17] provide theoretical confidence, but practical implementations may require additional robustness mechanisms to handle these real-world factors.

The slip angle results in Figure 9 demonstrate good stability, but occasional instances approaching the ±3 degree threshold suggest that near-limit handling conditions could benefit from further refinement in our model. Incorporating advanced tire models with varying friction coefficients could enhance performance in these edge cases, as suggested by the work of [15] on interpretable data-driven MPC for connected autonomous vehicles.

Future work should also explore the integration of our approach with connected vehicle technologies to leverage vehicle-to-vehicle and vehicle-to-infrastructure communication. This integration could enhance predictive capabilities beyond what is possible with a single-vehicle approach, potentially leading to further improvements in safety and efficiency. The hybrid approach demonstrated by [27] offers promising directions for such integration.

Additionally, while our current implementation achieves excellent tracking performance, the control energy efficiency (93%, as noted in our summary) suggests room for improvement in terms of optimizing control inputs. Exploring multi-objective formulations that explicitly balance tracking accuracy with energy consumption could enhance the overall efficiency of the system, particularly for electric autonomous vehicles where energy management is critical.

3) PRACTICAL IMPLICATIONS FOR AUTONOMOUS DRIVING

The exceptional performance of our KDE/KPCA-based MPC framework has significant practical implications for autonomous driving applications. The lateral tracking error of 0.0225 m demonstrated in Table 4 is well below the typical range of 0.05–0.10 m considered acceptable for lane-keeping systems, indicating that our approach could substantially improve safety margins in commercial autonomous vehicles. Similarly, the heading error RMSE of 0.0476 rad ensures precise directional control, essential for reliable navigation in complex urban environments.

The consistent performance across different scenarios shown in Table 5 addresses one of the most significant challenges in autonomous driving: maintaining reliable control across diverse operating conditions. The observed 81.3–89.8% improvement over traditional MPC approaches represents a transformational advance in capability that could accelerate the deployment of autonomous vehicles in commercial applications. This level of improvement aligns with the findings of [12], but our approach achieves significantly better absolute performance.

The computational efficiency of our approach (1.6 ms) has profound implications for hardware requirements in autonomous vehicles. This processing speed is well within the capabilities of automotive-grade ECUs, suggesting that our advanced control approach could be implemented without necessitating specialized computing hardware. This could substantially reduce the cost barriers to deploying sophisticated control algorithms in production vehicles, as discussed by [10] in their work on fast MPC implementation.

The intelligent speed adaptation shown in Figure 11, where the controller automatically reduces velocity in high-curvature regions, demonstrates the framework's ability to optimize the driving experience beyond mere path following. This behavior enhances both safety and passenger comfort, addressing key consumer acceptance factors for autonomous vehicles. Such adaptive behavior is particularly valuable for shared autonomous vehicles, in which passenger comfort is a primary concern.

The slip angle control demonstrated in Figure 9 has direct implications for vehicle stability and safety. By maintaining slip angles within ±3 degrees, our controller ensures stable vehicle dynamics even during challenging maneuvers, reducing the risk of loss of control. This stability is achieved without requiring complex vehicle dynamics models or extensive calibration, making our approach more scalable across different vehicle platforms than traditional methods.

The dimensionality reduction capabilities shown in Figure 14 address a fundamental challenge in autonomous driving: extracting meaningful features from high-dimensional sensor and state data. By capturing 95% of system variance with just two principal components, our approach significantly simplifies the control problem while preserving essential dynamics. This efficiency could enable more sophisticated scenario understanding and decision-making within the same computational constraints.

Our experimental results demonstrate that the proposed KDE/KPCA-based MPC framework not only advances the theoretical understanding of kernel-based methods for nonlinear control but also offers practical, implementable solutions for autonomous driving. The framework's exceptional performance in tracking accuracy, computational efficiency, and robustness across scenarios addresses key barriers to widespread autonomous vehicle deployment, with potential impact extending beyond academic research to commercial applications and transportation policy.

4) SENSITIVITY TO ASSUMPTION VIOLATIONS AND IMPROVEMENTS

While our KDE-KPCA framework offers significant advantages for autonomous vehicle control, it is important to acknowledge its limitations regarding underlying assumptions. Our analysis reveals that when distributional assumptions are violated, prediction quality deteriorates substantially- multimodality increases integrated squared error by 27%, heavy-tailed phenomena cause 34% underestimation of tail probabilities, and non-stationary dynamics elevate reconstruction errors by 42% across different driving regimes.

To address these limitations, we propose several enhancements for future work:

1) Robust Density Estimation: Developing adaptive kernel selection mechanisms that automatically switch between Gaussian, Student's t, and skew-normal kernels based on empirical distribution characteristics. This would provide natural robustness to heavy tails and skewness without manual intervention.
2) Multi-resolution KDE: Implementing a hierarchical bandwidth structure that maintains multiple resolution levels simultaneously, allowing the model to capture both global structure and local details without increasing computational complexity beyond $O(n \log n)$.
3) Transfer Learning Framework: Creating a meta-learning approach that leverages experience across different driving scenarios to rapidly adapt to distribution shifts using minimal data from new environments.
4) Uncertainty-aware MPC: Enhancing the MPC formulation to explicitly account for epistemic uncertainty in the density estimation, particularly in regions of the state space with sparse data or detected distribution shifts.
5) Hybrid Approaches: Combining data-driven KDE with physics-based models that maintain validity during extreme maneuvers where data-driven approaches typically struggle due to distribution extrapolation.

These improvements would address the framework's current sensitivities while maintaining its computational efficiency and adaptability for autonomous vehicle applications across diverse driving conditions.

VI. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper introduces a novel data-driven control framework designed for autonomous vehicle control and nonlinear system optimization. The framework combines Kernel Principal Component Analysis (KPCA), Kernel Density Estimation (KDE), Hankel matrix formulation, and Model Predictive Control (MPC) to address the challenges of system complexity and nonlinearities. The Hankel matrix structure is utilized to organize system dynamics, capturing temporal correlations and state transitions. KPCA is applied for efficient nonlinear feature extraction and dimensionality reduction, preserving 90% of system variance with only four principal components. KDE is used for robust state estimation and prediction, ensuring accurate state space representation. This integrated approach leads to significant improvements in tracking accuracy, computational efficiency, and energy efficiency, with lateral errors reduced by 38%, solving time reduced by 45%, and energy efficiency increased to 93%. Moreover, the framework maintains a reliable path completion rate of 99.5% even in complex environments.

In terms of practical implementation, the framework demonstrates several advances, such as efficient dimensionality reduction for real-time applications, adaptive parameter tuning for diverse operating conditions, and robust prediction capabilities. The preimage solution effectively solves the problem of reconstructing system states from the kernel feature space, ensuring accurate prediction and control synthesis while maintaining computational efficiency.

Future works could explore advanced kernel selection strategies to automatically identify optimal kernel functions for specific operating conditions, including adaptive kernel parameter tuning that responds to changing system dynamics. Composite kernels, combining multiple basis functions, could better capture complex nonlinearities present in autonomous vehicle dynamics, while incremental KPCA approaches could enable real-time updates of the feature space without complete recalculation. The Hankel matrix formulation could be extended to implement multi-resolution temporal modeling, capturing both fast and slow dynamics simultaneously. Wavelet-based decomposition could be integrated with the Hankel structure to provide frequency-selective representations of system dynamics, enabling more efficient prediction across different time horizons.

The KDE component could be enhanced with mixture models to better represent multimodal state distributions, particularly important for prediction under uncertainty or at decision points. Investigating robust KDE formulations would improve performance in the presence of outliers or sensor noise. Chance-constrained MPC approaches could maintain safety guarantees with probabilistic bounds, while multiscenario optimization could consider multiple possible future trajectories. Explicit MPC solutions could be precomputed for common scenarios to reduce online computational burden, while adaptive weighting schemes could dynamically balance competing objectives based on current operating conditions.

Reinforcement learning approaches could be integrated with the framework to enable autonomous adaptation to new environments without extensive retraining, including policy optimization for kernel parameter selection and MPC tuning. Deep learning could be used to approximate computationally intensive components of the framework, such as the preimage solution or feature mapping. Transfer learning techniques could facilitate knowledge transfer between different vehicle models or operating conditions, reducing data requirements for deployment in new scenarios. Domain adaptation methods could enable robust performance in varying road conditions, weather patterns, and traffic densities.

Distributed implementations of the framework would support multi-agent systems and vehicle platoons, enabling collaborative perception and control. Decentralized MPC architectures would allow for scalable deployment across multiple vehicles while maintaining coordination. Edge computing optimization would enable real-time performance on resource-constrained onboard systems. Formal stability and convergence guarantees could be developed for the integrated framework across its full operating envelope, including Lyapunov-based stability analysis for the closed-loop system and error bounds for kernel-based approximations.

Hardware-in-the-loop testing would provide valuable validation of the framework's performance under realistic computational constraints, while real-world deployment studies across diverse environments would verify the practical benefits of the approach. Human-in-the-loop validation would assess passenger comfort and trust in autonomous operation, and long-term studies would evaluate the framework's adaptation to seasonal changes and infrastructure evolution. These comprehensive enhancements would significantly advance the framework's capabilities while maintaining its core advantages in computational efficiency and control performance.

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