Freeway Traffic State Estimation using EKF-DFNN: Dual Correction Approach

***Abstract*.** One of the significant challenges in modern traffic engineering is accurate estimation of the traffic state, this involves precisely determining real-time traffic information, which is crucial for effective traffic management and the implementation of intelligent transportation systems. To address this challenge, various estimation algorithms have been developed, most of which are based on the Kalman filter and its variants, offering varying degrees of accuracy. In this paper, we propose an improved traffic state estimation algorithm based on dual state correction using the Extended Kalman Filter and a Deep Feedforward Neural Network (EKF-DFNN). The estimated traffic variables are then fed into a Support Vector Machine (SVM) classifier to predict the traffic state. The proposed algorithm is compared to a baseline approach that combines the standard Extended Kalman Filter with an SVM classifier. The results demonstrate that the proposed EKF-DFNN algorithm outperforms the classical EKF based method in terms of classification accuracy.

Keywords: Traffic state estimation, freeway traffic congestion, Extended Kalman filter, Deep Feed forward Neural Network.

1 Introduction

Intelligent transport systems (ITS) significantly contribute to the enhancement of transportation efficiency, safety, and sustainability. However, the availability of accurate data regarding the traffic variables such as flow, speed and density holds significant value for implementing effective intelligent transport systems, designed to traffic control and management strategies, including congestion mitigation systems. Nevertheless, the absence or inaccuracy of information concerning the current traffic state can give rise to critical challenges and complications. The primary solution to this issue entails implementing traffic state estimation systems (TSE).

TSE refers to the process of predicting traffic parameters (i.e., speed, density, and flows) based on a limited set of traffic variables that are collected from one or more detectors. This operation may ensure the sustainability of the traffic congestion detection system and helps to avoid errors and systems interruptions. Three fundamental components are considered to characterize the TES approaches: the estimation method, the traffic flow model, and the used input data. In this work we used the METANET model [1] to describe the dynamic behavior of the traffic flow in a given freeway section of the road based on the mean traffic speed and density, which are considered as input data.

Since the early 1970s, the estimation of traffic variables has attracted the attention of numerous researchers [2-4]. This process involves techniques that derive the traffic state by leveraging prior understanding of traffic conditions and partial observations. Recently, several estimation algorithms have been proposed in the literature, with the majority being based on the Kalman filter and its nonlinear extensions. The Kalman filter [5] is a widely used technique for recursive state estimation in various fields, such as signal processing, control systems, and robotics. Furthermore, it provides a systematic and efficient approach to estimate the state of a dynamic system by incorporating measurements and modelling uncertainties. The extended Kalam filter was commonly used in the literature for TSE approaches due to its ability to handle nonlinearities. In addition, some improvements were proposed in the literature to enhance the estimation efficiency using the EKF filter. One such enhancement was the introduction of the Iterated Extended Kalman Filter (IEKF) algorithm [6], which effectively tackles the problem of filter divergence that can emerge within the Extended Kalman Filter (EKF) algorithm. This divergence tends to manifest itself when noise is injected into the system and a disparity between observed data and estimated system state arises. In order to reduce the computational time requirement, the authors in [7] propose to use the Broyden's rank-one update procedure to approximate the time-varying Jacobian matrices of the process and measurements, which are necessary for the Extended Kalman Filter (EKF), at every time step. On the other hand, A.S.M. Bakibillah et al [8] proposed a novel adaptive-R Extended Kalman filter (AREKF) combined with a model-based data imputation technique to estimate traffic density. AREKF demonstrates its capability to precisely estimate density even in scenarios where the noise covariance matrices are not precisely determined. However, speed estimation was not considered in this study. The EKF approach has a major limitation, since it requires that the state variables should be represented only in vector form. This limitation greatly restricts its performance because it cannot accurately capture the complexities of multi-relational states in practice. To overcome this limitation, the authors in [9] introduced the Tensor Extended Kalman filter to handle various inputs, outputs, and state variables, all in flexible tensor formats. The proposed TEKF was applied to enhance the traffic prediction performance. Nevertheless, the algorithms that involve tensor operations inherently entail substantial computational complexities. Chenran Li et al. [10] introduced a methodology for state and parameter estimation that relies on the dual extended Kalman filter (DEKF) technique. This approach aims to attain precise states and time-varying parameters within a linear parameter varying system framework. The DEKF was constructed by using two separate filters: one for estimating the states and the other for estimating the parameters. The two filters were coupled through the state estimates, which are used as inputs to the parameter filter. This approach was constructed for model-based control in autonomous vehicles.

In the work of Zoran et al. [11], a feedforward neural network was integrated with an extended Kalman filter to accurately estimate the state of a robot's pose. The EKF was used to dynamically adjust and optimize the weights of the feedforward neural network. This innovative hybrid approach enables the system to continuously learn and update a motion model for the mobile robot in real-time.

In [12] the authors addressed the end-effector pose estimation problem of a tensegrity manipulator. The estimation procedure was based on the use of an extended Kalman filter and a deep feedforward neural network (FNN) with three hidden layers. The FNN was used before the EKF to improve the quality of the information acquired from marker measurements. Earlier, the authors in [13] proposed the utilization of a feedforward multi-layer perceptron, hereafter referred to as a feedforward neural network (FNN) to address the issue of correcting estimation errors of an EKF arising from non-geometric error sources, including link deflection errors and gear backlash, within the context of a robot positioning task. An identical approach was employed in reference [14], where the initial estimation of the elongation of a linear spring actuated by a shape memory alloy wire is accomplished through an EKF. Subsequently, this estimate is refined and corrected using an FNN.

Unlike the approaches presented in [11] and [12], where the DFNN was utilized before the EKF Algorithm, and in [13] and [14], where the DFNN was employed after the EKF Algorithm, we propose to integrate the DFNN within the EKF, positioning it precisely between the prediction and update steps. This enables us to carry out a dual correction of estimated traffic states, firstly using the DFFN and secondly using the EKF. To the best of our knowledge, no previous work has adopted the proposed EKF-DFNN combination for highway traffic state estimation.

The rest of the paper is organized as follows: in the section 2 we present the adopted ITS system and the proposed EKF-DFNN filter. The main obtained results are discussed in section 3, and finally a conclusion is provided in section 4.

2 Methodology

The road traffic state estimation system adopted in this work is illustrated in Figure 1. This system as introduced in [15] is specifically designed to classify the traffic flow within a freeway section as either free or congested. Fixed camera sensors have been installed individually along three distinct road sections (i-1, i, i+1), capturing traffic video recordings. Then the mean traffic speed and density are automatically measured using the image processing technique proposed in [16].

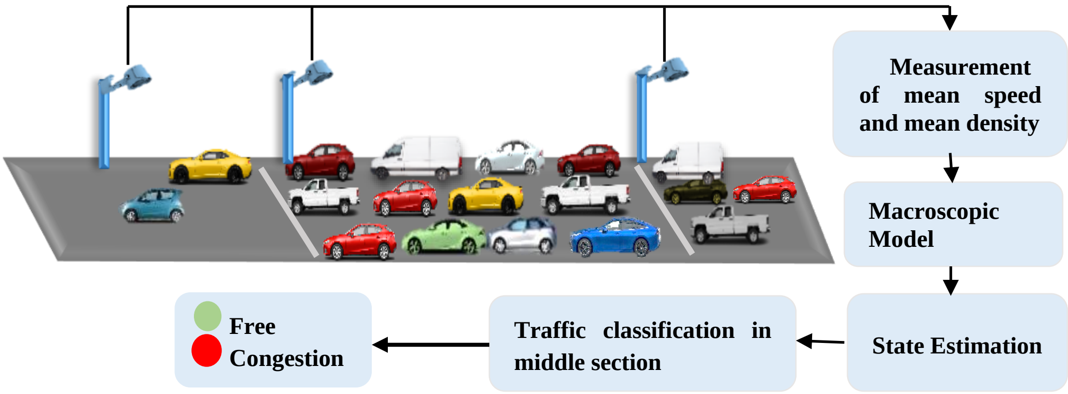


Fig. 1. The adopted intelligent transport system

2.1 Macroscopic model

The extracted traffic parameters from the three sections were used to calculate traffic speed and density aggregates according to the METANET model, as described by the following equations:

$$\rho_i(k+1) = \rho_i(k) + \frac{T}{\Delta_i \lambda_i}[q_{i-1}(k) - q_i(k) + r_i(k)] \quad (1)$$

$$v_i(k+1) = v_i(k) + \frac{T}{\tau}\left[V\big(\rho_i(k)\big) - v_i(k)\right] + \frac{T}{\Delta_i} v_i(k)$$
$$\times [v_{i-1}(k) - v_i(k)] - \frac{\nu T}{\tau \Delta_i} \frac{[\rho_{i+1}(k) - \rho_i(k)]}{\rho_i(k) + x} - \frac{\delta T}{\Delta_i \lambda_i} \frac{r_i(k) v_i(k)}{\rho_i(k) + x} + \xi_i^v(k) \quad (2)$$

$$V(\rho) = v_f exp\left[-\frac{1}{a}\left(\frac{\rho}{\rho_c}\right)^a\right] \quad (3)$$

where :

Δ_i is the length of section i; T is the model time step;

$\rho_i(k)$, $v_i(k)$, $q_i(k)$, and $r_i(k)$ are, respectively, the vehicle density, the average speed, the traffic flow, and the on-ramp inflow, all in section i at time kT; v_f and ρ_{cr} are, respectively, the free speed and the critical density; a is an exponent parameter; λ_i denotes the number of lanes in section i; τ is a time constant; ν is an anticipation constant; δ is an on-ramp constant, x is a constant parameter used to keep the third and fourth terms limited when ρ_i becomes small; $\xi_i^v(k)$ and $\xi_i^q(k)$ are zero mean white Gaussian noises added to reflect the modeling inaccuracies.

Eq. (1) describes the conservation of vehicles. It is, therefore, unaffected by noise.

2.2 Traffic State Estimation

The Extended Kalman Filter is integrated with a Deep Feedforward Neural Network, in this work, to enhance the traffic state estimation accuracy. The proposed EKF-DFNN scheme is presented in Figure 2.

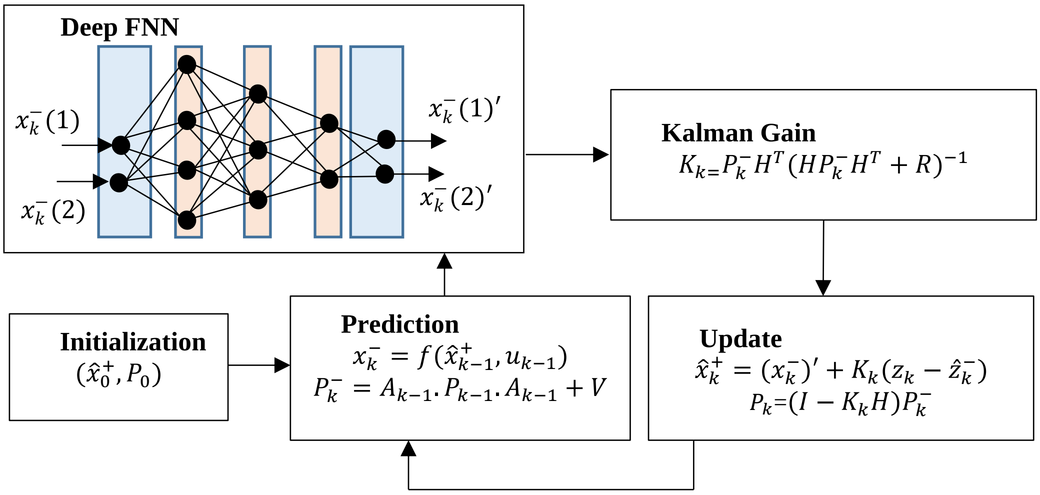


Fig. 2. The proposed EKF-DFNN blocks diagram

In this Figure:

- (x_k, P_k) are, respectively, the state space vector and the corresponding covariance matrix at time kT, with:

$x_k = \begin{bmatrix} \rho_i(k) \\ v_i(k) \end{bmatrix}$,

where $\rho_i(k)$ and $v_i(k)$ are, respectively, the speed and the density at time k in highway section i.

- f is the nonlinear function that relates the state vectors x_k and x_{k-1}:

$x_k = f x_{k-1} + u_k$,

where u_k is the process noise, assumed to be white and Gaussian, with zero mean.

- A denotes the matrix of the partial derivatives of f with respect to x, defined as:

$A_{k-1} = \left.\frac{\partial f_{k-1}}{\partial x}\right|_{\hat{x}_{k-1}^+}$

- H denotes the measurement matrix, given by:

$\mathrm{H} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$;

- R and V represent the measurement noise and the process noise covariance matrices.

Since its computational time is reduced compared to other nonlinear filters, such as the particle filter and ensemble Kalman filter, the EKF has been used in various other real-time applications, such as navigation systems. Furthermore, the extended Kalman filter reduces the problem of nonlinear filtering to that of linear filtering by linearizing the state and measurement equations. The equations which govern it are those of the linear Kalman filter in which certain matrices are replaced by Jacobian matrices. However, in practice, the use of the EKF has a well-known drawback: the process of linearization can lead to a highly unstable filter.

To overcome this issue, we propose in this work to first correct the predicted state space using the DFNN, and then apply the linear correction formula of the EKF filter, as depicted in Figure 2.

The feed forward neural network is a fundamental neural network model, in which each unit receives input solely from the previous layer and forwards it to the next layer, allowing data to flow sequentially through the network. Moreover, the FNN serves as the foundational architecture for various other neural network models, including convolutional neural networks, radial basis functions, and many others.

The deep FNN network adopted in this work comprises an input layer, followed by a number of hidden layers, then, an output layer. All these layers are fully connected. The dimensionality of the input layer is two as well as the output layer, including the mean traffic speed and the mean traffic density.

3 Results and Discussion

In this work we used the US (United States) Highway 101 (US 101) video dataset, also known as the Hollywood Freeway, which was collected by researchers of the NGSIM (Next Generation SIMulation) program in Los Angeles (NGSIM dataset 2005) [17]. This dataset includes videos captured by various cameras placed at different sections of the highway.

Firstly, each 15-minute video segment is divided into shorter sequences lasting 5~6 seconds. This process resulted in a total of 166 video sequences for each highway section. Each video sequence comprises 58 to 61 frames, recorded at a rate of 10 frames per second, with a resolution of 320 × 240 pixels.

Fig. 3. Example of frames from the US 101 traffic video dataset. The sample frames depict two traffic conditions in the middle section, coarsely categorized as light (top row) and congested (bottom row).

Subsequently, a hand-labeled ground truth that characterize the traffic conditions within the middle section of the highway was established. Based on this ground truth, the 166 videos were categorized into two classes: 109 videos representing heavy traffic conditions (characterized by slow or stop-and-go speeds) and 57 videos depicting light traffic conditions (representing normal speeds) [15]. In Figure 3, we present a representative selection of video clips from this dataset. The extent of the full highway including the three section is presented in Figure 4.

The raw measurements, which are the mean traffic speed and mean traffic flow, were extracted from the video sequences using the method presented in [16].

The parameters of the macroscopic traffic flow model were set as in [15] as well as the measurement and the process noise covariance matrices for the EKF filter. The initial state vector was set equal to the first measurement vector, and the covariance matrix was set to:

$$P_0 = \begin{bmatrix} 0.01 & 0.1 \\ 0.1 & 1 \end{bmatrix}.$$

Exit (i+1) Middle(i) Entry(i-1)

Fig. 4. Sections of the studied road.

The predicted state vector was injected in the DFNN model to perform a prior smoothing of the measures as illustrated in figure 5.

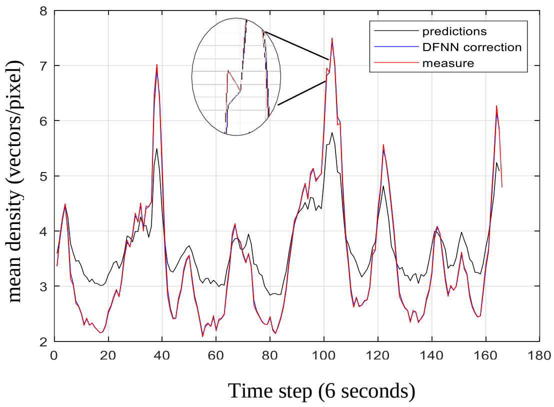


Fig. 5. DFNN correction

The DFNN training step was performed using the measured vector and the corresponding estimated vector.

The following pseudo-code explains the running of the proposed DFNN-EKF algorithm.

```
Xe=X0                     //initial state
For i=1 to N              // number of measures
     Pe=Prediction        // using EKF
     Net=Training (measure(i), Xe)    // DFNN
     X=Simulation (Net, Pe)           // DFNN
     Xe=Update(X)                     //using the EKF
     Save (Xe)
end
```

To assess the proposed state estimation approach, we input the estimated state vectors into the SVM classifier to classify the traffic into two classes: free and congested.

The classification procedure was carried out using a 4-fold cross-validation methodology. This means that we allocated 75% of the dataset for training and kept 25% for testing. Using trial and error, it was found that for the SVM, a radial basis function Kernel (RBF) and the Gaussian Kernel give the best results.

The DFNN network was trained using a function that updates weight and bias values according to the resilient backpropagation algorithm. We conducted several tests using different numbers of hidden layer ranging from 1 to 8, and an arbitrary selection of neurons numbers.

Table 1 presents the obtained classification accuracies. It can be observed from this table that the best classification result was obtained with 5 hidden layers.

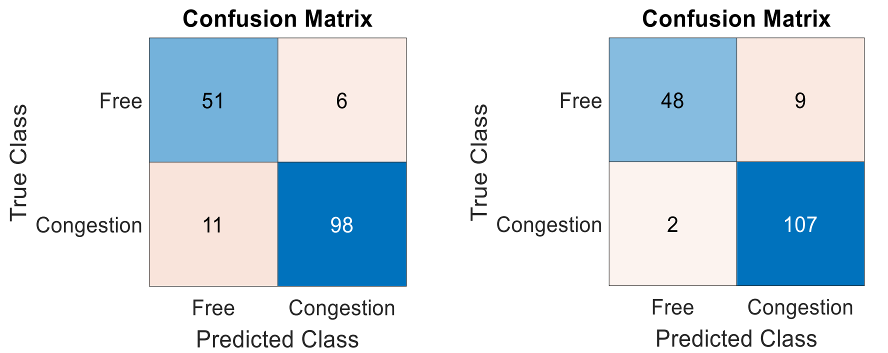
In table 2 we compare between this result and the result obtained using the classical EKF, as reported in [15]. As it can be observed, smoothing the noisy measurement by either the EKF or the DFNN-EKF improves the classification accuracy. It can also be observed that integrating a DFNN into the EKF, enhances the performance. It mainly improves the detection of the congestion, as can be seen in the confusion matrices presented in Figures 6.

TABLE I. CLASSIFICATION ACCURACY VS NUMBER OF LAYERS

Number of layers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Numbers of neurons	20	20,15	20,15,5	20,15, 10,5	20,15, 10,5,4	20,15, 10,5,4,3	20,15, 10,5,4, 3,2	20,15, 10,5,4, 3,2,1
Accuracy (%)	90.99	92.78	92.78	92.18	93.37	88.02	90.99	88.02

TABLE II. EKF VS EKF-DFNN

	Measurements	EKF [15]	EKF-DFNN
SVM classification accuracy	84.61%	89.77%	93.37%



(a) EKF/SVM

(b) EKF-DFNN/SVM

Fig. 6. Confusion matrix of traffic classification

4 Conclusion

Accurate estimation of traffic conditions contributes to build safer and more efficient transportation networks. In this paper, we propose an approach to address the challenges of traffic state estimation, particularly in dynamic and noisy real-world environments. The proposed approach is based on the combination of the Extended Kalman filter and the Deep feedforward neural network. As a result, the predicted vector state benefits from dual correction instead of just one, leading to an enhancement in traffic classification accuracy. The suggested method is suitable for real-time applications because the EKF runs in parallel with the DFNN.

In terms of perspective, our goal is to further refine and enhance this approach to achieve even greater accuracy in traffic state recognition by incorporating more sophisticate deep learning architectures.

5 References

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