Adaptive Illumination : Vehicle Tracking in Bridges with Surveillance Cameras

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Abstract

The paradigm shift towards autonomous control systems, introduced with themes that we are becoming increasingly familiar, such smart cities and autonomous driving, in addition with the growing interest in energy consumption minimization and in development of automatic surveillance technologies allows to introduce and exploit adaptive lighting systems totally independent of human operators for spaces of public interest such as bridges and tunnels.

In this work an architecture of an autonomous lighting system that through sensing with surveillance cameras, vehicles detection and tracking produces the necessary illumination to each vehicle, is presented. The main focus lies on vehicle tracking and lighting optimization.

A performance study of the tracking results is made in order to analyze the relevance of precise modeling of the vehicles behavior.The influence of data acquisition rate and of measures associated noise on filter performance is also studied. Two algorithm proposals that aims to obtain the optimal illumination configuration for a given road infrastructure while guaranteeing the safety of its users are presented and compared.

Keywords: Extended Kalman Filter, Motion Models, Vehicles Tracking, Linear Optimization, Dimming, Adaptive Illumination

I. Motivation

In recent years, concern about environmental issues has been a topic thoroughly covered. Power consumption is the source of 80% of emissions of greenhouse gases in the European Union (EU), so naturally emerges as one of the highest priorities to be minimized. The rational use of energy and the energy efficiency in public lighting systems are part of these objectives.

It is noted nowadays the fluent and growing emergence of user-friendly solutions, combined with more efficient energy management for all market sectors and production processes. Public lighting systems are no exception, there are solutions in terms of hardware that applied in places where the technologies are obsolete would lead to greater energy efficiency. This work takes advantage of the advances and innovation on promising hardware and focuses on the study of lighting management techniques for outdoor lighting systems with the objective of provide structural savings on public illumination sector.

Infrastructures such as bridges and tunnels are usually equipped with surveillance cameras. The extraction and processing of data through these cameras may allow design systems capable of adjust lighting to the occupation of the road as well as extract additional information to increase safety levels.

II. Problem Formulation

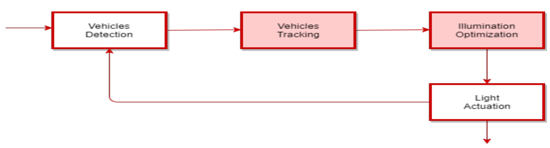
This work addresses the problem of minimizing energy consumption in public spaces such as bridges and tunnels. The basis thesis for the current work can be found in the bibliography [1]. A structure of a system that would make it possible to minimize the expenses with lighting during the night was engineered, taking as example the Vasco da Gama Bridge. The system consists of using a set of luminaries with dimming capabilities that adjust to the occupancy / non-occupation of the bridge segments by vehicles, in real time. To do this, it is necessary to have a set of sensors to determine the occupation of the bridge, which is choose to be surveillance cameras, since it is an economically viable and robust option.

Through the techniques of image processing and calibration of the cameras it is possible to extract the position of the vehicles on the bridge: Vehicles Detection.

In order to achieve a better position estimate of the vehicles position, their trajectories are filtered. This process is a part of the Tracking process.

After the vehicles position be correctly identified in the bridge, a global minimization method with constraints that allows to minimize the energy consumption while guaranteeing the safety of the occupants is applied.

This following study aims to focus mainly on two themes: Vehicle tracking and optimization techniques.



The study of vehicle behavior is a widely explored topic.

Being able to identify and follow a vehicle in a robust way can help in the management of this kind of public spaces through the collection of statistics and the identification of driving patterns and can contribute to increase the safety of all users through detection of offenses, deviant behaviors and accidents.

By increasing accuracy it could even come to the point of predicting motorist behavior, which could be used to enhance security in areas that are increasingly impacting civil societies, such as the prevention of terrorism.

We will focus on robust filtering of vehicle trajectories, which are noisy, using the most widely used tool for this purpose: Kalman Filters. Since the behavior of a vehicle is given by a non-linear model, we use an EKF, using and comparing two motion models: Car Model and Unicycle Model.

Another purpose of this work is to address the problem of lighting optimization.

In order to be able to reach improvements to the option already introduced, another algorithm that are having promising results in interior lighting will be studied, and with suitable modifications, adapted to the reality under study.

III. Related Work

As already mentioned, [1], provides the basis of the system architecture.

LED based luminaires have key-features like energy efficiency, flexible tunabillity, capability of dimming and long lifetime that make them be the prevailing trend in lighting control systems, [9]. The continuous improvements in the luminaires lead to lighting optimization being increasingly studied.

The most interesting approaches in this field are made for interior lighting purposes. There is a extensive and substantial work in this area such the proposes in [7] , [2] and [8].

However companies in the outdoor lighting sector already recognize that lighting control systems have a very promising future.

The vehicle tracking problem has been widely studied . The contribution of the work in [10] and [11] in derivation and explanation of the Extended Kalman Filter forms a great basis for work development in this field.

In order to perform and compare vehicle tracking for distinct motion models, these are formulated using as basis the work developed in [4].

IV. Extended Kalman Filter

For a Gaussian Linear system the most widely used method for state estimation is the Bayesian tracker Kalman Filter, [6], which provides an optimal estimation of the system state. However most practical systems have nonlinearities.

To address the problem of vehicle tracking on public roads it is used the Extended Kalman Filter, the extended form of KF, a recursive estimator of the system state, conceived to deal with nonlinear dynamics by linearization of first order Taylor series expansion. Due to the linearization, the EKF is no longer optimal but is still the most common approach to deal with nonlinear systems. The filtering problem is written as

$$\begin{cases} x_{t+1} & = & f(x_t, \xi_t) \\ z_{t+1} & = & h(x_{t+1}, \eta_{t+1}) \end{cases} \tag{1}$$

where:

- x_{t+1} is the system state at instant $t+1$. For a vehicle the system state is compound by the descriptors of its motion at instant $t+1$
$$x_{t+1} = \begin{bmatrix} \chi_{t+1} & y_{t+1} & \theta_{t+1} & v_{t+1} & w_{t+1} \end{bmatrix}^T$$
where χ_{t+1} is used to represent the first component of the vector x_{t+1} and therefore avoiding to repeat the same variable name.
- z_{t+1} is the observation/ measured data at instant $t+1$;
$$z_{t+1} = \begin{bmatrix} \chi_{t+1} & y_{t+1} & \theta_{t+1} \end{bmatrix}^T$$
- ξ_t and η_{t+1} are, respectively, the system and measurement error vectors that convey the uncertainties and errors associated with system state model and data collection process. ξ_t and η_{t+1} have covariance matrices R_t and Q_t, respectively.
- $f(x_t, \xi_t)$ is the system state dynamics function, a non-linear function of the previous state system, x_t, and the system error, ξ_t. In chapter VI-B several motion models, that particularizes the system state dynamic for the subject of interest, are presented;
- $h(x_{t+1}, \eta_{t+1})$ is the measurement function, a nonlinear function of the state system, x_{t+1}, and the observation error, η_{t+1}.

The main goal of the filter is to obtain the best estimate of the state x_{t+1}, using as minimization criteria the mean-square state estimate error, but because state and observation dynamics, $f(.)$ and $h(.)$ respectively, are nonlinear functions, the optimization criteria can not be directly applied. Extended Kalman Filter do the linearization of nonlinear dynamics around previous state estimates, avoiding high computational effort needed otherwise. Thus, EKF is not an optimal approach because it is implemented on a set of approximations and will not produce the exact posterior state estimate in the optimization criteria sense, but is broadly used in real-time applications.

EKF consists in two phases:

1) The Predict Phase produce an estimate of the state and covariance for the next timestep, using the state estimate of the current step.
2) In the Update Phase the measurement information z_{t+1} is included to achieve a more accurate state estimate and covariance.

a) Initial State: The initial state x_0 is the vector that characterizes the system at initial instant t_0. It has a probability distribution function completely characterized by the mean vector μ_0 and the covariance matrix Σ_0 (the only available information at initial instant).

Following the optimization criteria the initial optimal state is $x_0^o = \mu_0 = E[x_0]$, thus, the error covariance of the estimate is $\Sigma_0^o = E[(x_0 - x_0^o)(x_0 - x_0^o)^T]$.

A. Prediction Phase

At the end of the Prediction Phase we get the predicted state and the predicted estimate covariance:

$$\begin{cases} \widehat{x}_{t+1} & \simeq & f(x_t^o) \\ \widehat{\Sigma}_{t+1} & = & J_{f(x_t)} \Sigma_t^o J_{f(x_t)}^T + Q_t \end{cases} . \quad (2)$$

B. Update Phase

Following [11] it is assumed that the optimal estimate of the state x_{t+1}^o at instant $t+1$ is a linear combination of the predicted state $\widehat{x}_{t+1}$ and the measure obtained at the same instant z_{t+1}

$$x_{t+1}^o \quad = \quad a + K_{t+1} z_{t+1}. \quad (3)$$

The main goal is to find a value of x_{t+1}^o, at instant $t+1$, nearest as possible of the real x_{t+1}

At the end of the update phase, the state and estimate covariance and are:

$$\begin{cases} x_{t+1}^o & = & \widehat{x}_{t+1} + K_{t+1} \underbrace{(z_{t+1} - h(\widehat{x}_{t+1}))}_{Innovation\ residual, \widehat{y}_{t+1}} \\ \Sigma_{t+1}^o & = & (I - K_{t+1} J_{h(\widehat{x}_t+1)}) \widehat{\Sigma}_{t+1} \end{cases} \quad (4)$$

where

$$K_{t+1} \quad = \quad \widehat{\Sigma}_{t+1} J_{h(\widehat{x}_{t+1})}^T (S_{t+1})^{-1}, \quad (5)$$

and

$$S_{t+1} \quad = \quad J_{h(\widehat{x}_t+1)} \widehat{\Sigma}_{t+1} J_{h(\widehat{x}_t+1)}^T + R_{t+1}. \quad (6)$$

C. Extended Kalman Filter Tuning

The Extended Kalman Filter uses mathematical models to model the dynamics of the system and sensors, called the system model and observation model.

Equations describing system behavior, including motion models, are imperfect as are sensors, which are noisy sources of data. Hence the need to assign degrees of uncertainty to each of the models.

Since the Kalman filter is a Gaussian filter, the probabilistic representation of the uncertainty is represented parametrically by the mean and covariance. The choice of system model error covariance matrix, Q, and observation model error covariance matrix, R, is the filter calibration process. The filter is correctly calibrated when the values of Q and R are found so that the filter produces an estimate as close as possible to the effective trajectory of the vehicles.

The calibration of the filter is probably one of the biggest challenges to its use.

The estimation of the previously mentioned matrices can be viewed as the following optimization problem:

$$\min_{Q,R} \left(\sum_{i=1}^{N} \sqrt{(x_i - \widehat{x}_i(Q,R)^T)(x_i - \widehat{x}_i(Q,R))} \right)^T .a, \quad (7)$$

where N is the total number of trajectory coordinates, x_i is the is the state vector for at time instant i , $\widehat{x}_i$ is the estimate state vector at time instant i and a is a weight vector for the error in each dimension.

Typically the covariance matrix of the measurement error is set equal to the Gaussian noise covariance matrix of the measurements and then find the system model error covariance matrix that minimizes the difference between the original state vector and the estimated state vector.

Thus, the optimization problem is reduced to:

$$\min_{Q} \left(\sum_{i=1}^{N} \sqrt{(x_i - \widehat{x}_i(Q)^T)(x_i - \widehat{x}_i(Q))} \right)^T .a \quad (8)$$

V. Linear Programming

Linear programming or linear optimization problem is an optimization technique of a linear objective function when all the constraints on the variables, equalities or inequalities, are also linear.

Linear programs are convex optimization problems which means that any local optimizer is also a global optimizer. However a linear program can have more than one optimal solution.

Its feasible region is a convex polytope, defined as the intersection of finitely many half spaces, where each is defined by a linear inequality.

In matrix-vector notation, a linear program in standard form can be written as

$$\begin{aligned} & minimize\, z = c^T x \\ & {\scriptstyle subject\, to} \begin{cases} Ax & = & b \\ x & \geq & 0 \end{cases} \end{aligned} \quad (9)$$

with $b \geq 0$. x and c are vectors with lenght n, A is the constraint matrix with dimension $m * n$ and b is is a vector of lenght m. This will be the form of a linear program used within the simplex method.

Accordingly with [5], the Simplex Method is the most widely used method for linear programming and one of the most widely used of all numerical algorithms.

VI. Illumination Optimization

Without loss of generality for other applications, we will consider the application of lighting systems to a bridge.

The first goal is to propose a comparison algorithm, that is, even if not the best approach to the setting in question, allows to form a basis for future comparisons and then propose an alternative that better address the problem previously presented.

Considering the illumination system of a traffic direction of the bridge with **M** LED luminaires, equidistant from each other, by a distance **L**, wherein each lamp has a dimming level that varies in a range set between zero and one, represented by vector **x**, the $M \times 1$ dimming vector for the luminaires:

$$x = \begin{bmatrix} x_1 & x_2 & \cdots & x_M \end{bmatrix}^T \quad , \quad x_i \epsilon \begin{bmatrix} 0 & 1 \end{bmatrix}. \quad (10)$$

The value x_i=0 means that the LED luminaire is dimmed off completely and $x_i = 1$ means that the luminaire is at its maximum light intensity.

The luminance scales linearly with the dimming level if the measured luminance value is taken as the output and the dimming level as the input [3]. It is thus reasonable to assume that each luminaire produces a triangular shape of light intensity given by:

$$h(d) = \begin{cases} 1 - \left|\frac{d}{d_{rng}}\right|, & if\,|d| < d_{rng} \\ 0 & otherwise, \end{cases} \tag{11}$$

where $h(d)$ denotes the luminance intensity at distance d measured on the bridge driving plane and d_{rng} indicates the lamp working range $[-d_{rng}, d_{rng}]$. It is considered that $d_{rng} \geq L$, otherwise one gets a darker region in between the lamps, which has a minimum luminance intensity at $d = L/2$ with the value $h(L/2) + h(L/2 - L) = 2 - L/d_{rng} < 1$.

In all the approaches proposed is considered that communication is perfect, i.e., there is no packet loss and sending time is disregarded.

Hereupon, start to present proposals for centralized illumination optimization which is expected to enable the most efficient light configuration at any instant of time, **t**, and therefore, allow the greater energy saving, which leads to a more significant expense decrease.

As proved in [2], the minimization of the total power consumption is equivalent to the minimization of the sum of the dimming levels of LEDs.The illumination intensity of a LED is typically controlled using PWM so the dimming level x_i is the duty cycle of the PWM waveform. Thus the average power consumed by the i_{th} LED over one waveform cycle $P_i(x_i)$ is given by

$$P_i(x_i) = x_i P_{on} + (1 - x_i) P_{off} \tag{12}$$

where P_{on} and P_{off} are the power consumptions while the LED is on and off. Since in practice $P_{off} = 0$, 12 becomes

$$P_i(x_i) = x_i P_{on} \tag{13}$$

The total power $P_T$consumed by the lighting system is the sum of the average power consumed by each LED

$$P_T = \sum_{i=1}^{M} P_i(d_i) \tag{14}$$

Thus, the minimization of the total power is equivalent to the minimization of the sum of all dimming level of LEDs

$$\underset{x_i}{arg\,min} \sum_{i=1}^{M} P_i(x_i) \equiv \underset{x_i}{arg\,min} \sum_{i=1}^{M} x_i \tag{15}$$

The main goal is to obtain the optimal vector x^*, through the minimization of the sum of all dimming levels, which as seen is proportional related with consumption, satisfying the constraint of the physical limits of the luminaires and ensuring the minimum necessary luminance.

The sufficient necessary luminance lighting to illuminate each vehicle is defined as a triangular illumination window centered on the center of mass of each vehicle.

Consider the matrix B, of dimension $n \times K$, that represents the application of the illumination mask to each vehicle in the bridge

$$B = \begin{bmatrix} h_{v1} & | & h_{v2} & | & \cdots & | & h_{vK} \end{bmatrix}_{n \times K} \tag{16}$$

where K is the number of vehicles in the bridge and h_{vk} is a column vector with n elements showing the window of the necessary light for vehicle number $k \in \{1, \cdots, K\}$. More precisely, a vehicle located at position p_k implies non-null entries around location p_k on the column vector h_{vk}, of length n the number of segments in which the bridge was divided. Considering the length of the bridge to be between the first and the M_{th} lamp, then one has that the maximum number of sampling points in the bridge, n is defined by the relationship $(n-1)\delta = (M-1)L$ or

$$n = \frac{(M-1)L}{\delta} + 1, \tag{17}$$

where δ the discretization parameter of the bridge.

Assuming that the illumination required by each vehicle is equal to the illumination pattern produced by one lamp, 11, then

$$h_{vk} = \begin{bmatrix} h(0 - p_k) & h(\delta - p_k) & \cdots & h((n-1)\delta - p_k) \end{bmatrix}^T \tag{18}$$

where p_k denotes the location of the k^{th} vehicle.

It is thus constructed the reference b, of dimension $n \times 1$.The column vector b is the equivalent of merging all the illumination windows applied to all vehicles in the bridge, so b can be defined as the maximum of B at every row, $b_n = max\,B(n,:)$.

$$b = \begin{bmatrix} b_1 & \cdots & b_n \end{bmatrix}^T. \tag{19}$$

A. Initial approach of centralized optimization

The following approach is proposed by [1]

$$x^* = arg_x\,min \sum_{i=1}^{M} x_i \quad , \; i = 1, ...M \quad . \tag{20}$$
$$\text{s. to} \quad x \text{ is adequate for vehicles on the bridge}$$

This approach considers that the illumination system comprises:

- A central controller with a communication module that receives the reference vector and sends the result of optimization corresponding to each lamp;
- All the fixtures have a communication module that receives dimming level proposed by the controller;
- Occupancy sensors (cameras);

The reference generator receives as input a detection vector and produces a reference to controller, i.e. create a vector with the luminance required in each segment of the bridge.

The reference generator receives the detection result and applies to each vehicle an illumination window.

When the distance between vehicles is small enough, the windows merge, and the resulting window, at each point assumes the maximum value of the windows that generate it.

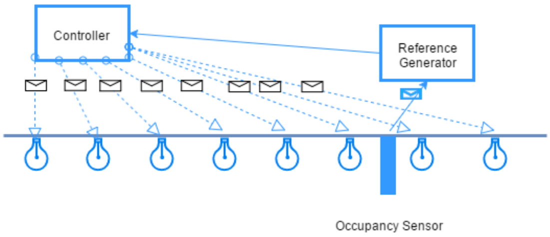


Figure 1: High level diagram of the initial approach of centralized optimization

The 20 can now be represented in matrix form.

$$x^* = arg\,min\; 1^T d \tag{21}$$
$$s.to \begin{cases} Ax \geq b \\ 0 \leq x_i \leq 1,\ i = 1, ..., M \end{cases}$$

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B. Centralized optimization with daylight adaptation and uniformity contrast

The European standard EN 13201 sets out the compelling standards for public lighting projects and recommends the photometric parameters for each type of application.

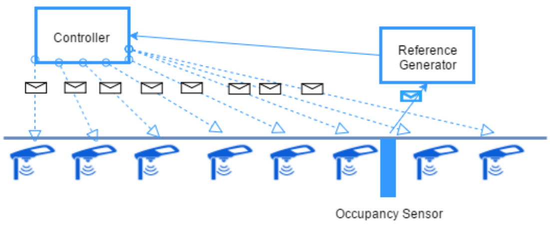


Figure 2: High level diagram of the second approach of centralized optimization

Without going into further details, which deviate from the purpose of this thesis, the above-mentioned standard recommends minimum values of illumination uniformity, maximum disturbing glare and minimum surrounding lighting, which means it is not necessary to achieve absolute values of illumination for each segment of the bridge but either is not necessary to guarantee that the contrast between segments lies below a fixed threshold.

Knowing that is not necessary use completely uniform illumination, as tried in the previous proposal, but rather create lighting zones complying with the standards it is suggested a system with a similar architecture than previous one but where the controller has a different role. The new optimization suggestion also considers daylight illumination , which helps to reduce wastage on sunsets and sunrises periods.

To take advantage of the daylight is necessary to disaggregate this one from the artificial light. A sensing solution for this purpose is proposed in [13].

First have to define some notation, as zone. If we consider the scenario without light interference is easy to imagine the division of bridge into lighting zones, i.e sequent sections illuminated by m^{th} lamp. In real case, where the resulting illumination at a stretch is the sum of several light luminaires, the division into zones of lighting is not as intuitive as previous. The zone setting criterion in this case is based on the fact that the light linearly decay with the distance from the fixture, which implies that the area closest to the n_th lamp has greater contribution from this luminaire than from its neighbors. The behavior of LED is assumed to be approximated by a triangle:

$$h(n) = \begin{cases} 1 - \left|\frac{d}{d_{range}}\right| & if\ |d| < |d_{range}| \\ 0 & otherwise, \end{cases} \tag{22}$$

where d is the distance to the lamp and d_{range} is the longitudinal range of the lamp. So, at each m_{th} luminaire, corresponds a zone. There are N zones, the same number of zones and fixtures ($M = N$), and are defined n points that represent the n segments of interest to illuminate.

[wang2012distributed] presents a centralized version of an algorithm that assume the same premises but instead of simulate the behavior of light mask, which can be deployed to various zones without necessarily include some complete zones, proposes a binary assignment occupancy / non-occupancy for each zone and then optimizes the lamp setting for each zone such that each zone meets the uniformity parameters. Here will be presented a modification of this algorithm so that the illumination window concept remains valid, and do not have to over light segments of a zone that does not belong to the lighting window. Let **S** be the set of continuous segments that are occupied or unoccupied, i.e if there are **J** light windows of illumination, and **K** spacings between them and extremities, then $S = J + K$. Let R_j be the set of points of **S** wherein R_1, R_2, ...,R_J are the points of occupied segments and $R_(J+1)$, $R(J+2)$,..., $R(J+K)$ are the points of unoccupied segments. C_o and C_u are the goal uniformity levels and $(1 - C_o)L_o$ and $(1 - C_u)L_u$ are maximum negative deviation of the average lighting level L_o or L_u, respectively for occupied and unoccupied segments.

$$x^* = arg\,min \sum_{m=1}^{M} x(m)$$
$$s.to \begin{cases} \frac{1}{M}\sum_{(x_j,y_j)\in R_j} E_T(x_j,y_j) \geq L_o, j = 1, 2, ..., J \\ E_T(x_j,y_j) \geq (1 - C_o)L_o, \forall(x_j,y_j) \in R_j, j = 1, 2, ..., J \\ \frac{1}{M}\sum_{(x_j,y_j)\in R_j} E_T(x_j,y_j;x) \geq L_u, j = J+1, J+2, J+K \\ E_T(x_j,y_j) \geq (1 - C_u)L_u, \forall(x_j,y_j) \in R_j, j = J+1, J+2, J+K \\ 0 \leq x_i \leq 1,\ i = 1, ..., M \end{cases}$$

where $E_T = \sum_{i=1}^{M} A(x,y)x_i + D(x,y)$. sectionCars Tracking This section presents the techniques that will be studied, implemented and compared to track the vehicles on the bridge.

As presented in III, $f(xt, \xi_t)$is the system state dynamics function, a nonlinear function of the previous state system, that particularizes the system state dynamic for the subject of interest. In this concrete case what is intended to be modeled is the behavior of a vehicle, which is why we have opted for the particularization of the Unicycle and Car Motion Models.

Motion models are necessary to predict target moves and so the need to understand several models and applications arises.

The main goal is to understand the Kinematic Model of a Unicycle and of a Car.

The kinematic model of a vehicle lets us know the linear velocity and the angular speed of it, at any instant of time, regarding the speed of the wheels.

Holonomic systems are characterized by the independence of the system result and the path taken to reach some state. So, a system that can move in any direction, at any configuration, is an holonomic system.

A vehicle has some motion constraints, generated by the kinematics, so has limitations on the directions it can take when moving, at an arbitrary configuration. For instance, if we consider a four wheel vehicle with two frontal wheels that roll but don't slide and two back wheels that slide but don't roll we can conclude that the vehicle's wheels are not designed to slide sideways because the back wheels would have to slide instead of roll.

Therefore, the system cannot move in any direction, it has limitations, and so the result depends on the path taken to reach some state. Those are called non-holonomic systems.

There are several kinematic models that can approximate the behavior of a vehicle, depending on the subject of interest. In this case, we are looking for a model to simulate the behavior of a car on a bridge, so we are not concerned , for instance, in general forces or torques.

For studying motion models we'll need to do some assumptions:

1) The contact between the road and the wheels is reduced to a point;
2) There is no slippage between the wheels and the road;
3) The plane of the wheels is always perpendicular to the road;
4) It is assumed that the vehicle is a rigid body;

Let's start for the simpler case: The Unicycle Model.

C. Unicycle Model

A unicycle is basically a wheel that rolls on a plane, while its body is kept orthogonal to that plane.

Its configuration can be described by a vector q with three coordinates:

1) (x, y): position coordinates of the wheel's point in contact with the plane;
2) θ: orientation of the wheel relatively to the x axis;

The differential kinematics gives us the transformation between velocities described in the wheels frame and in the vehicle frame.

a) Unicycle Model Discretization: Leapfrog-Integration allows to obtain a discrete-time representations of continuous-time models.

The previously obtained motion model can be converted into discrete-time model using this method.

$$\begin{cases} x_{t+1} = x_t + TVcos(\theta_t + \frac{T}{2}w) \\ y_{t+1} = y_t + TVsin(\theta_t + \frac{T}{2}w) \\ \theta_{t+1} = \theta_t + Tw \end{cases} \tag{23}$$

D. Car Model

x_r, y_r: cartesian coordinates of the center of the rear axis;
x_f, y_f: cartesian coordinates of the center of the front axis;
L: distance between both axis;
θ: orientation of the vehicle regarding the x axis;
ϕ: steering angle;
v_f, v_r: linear velocity of the wheels

To study the kinematic model of the car we need some extra considerations:

1) Frontal wheels are steering wheels but have no traction;
2) Back wheels are traction wheels that won't steer;

It's possible to write down the model for the central point of the frontal axis (24):

$$\begin{cases} \dot{x_f} = v_f cos(\phi + \theta) \\ \dot{y_f} = v_f sin(\phi + \theta) \\ \dot{\theta} = \frac{v_f sin(\phi)}{L} \end{cases} \tag{24}$$

E. Car Model Discretization

The model (24) previously obtained can be converted into discrete-time model using Leapfrog Integration Method, as previously.

$$\begin{cases} x_{t+1} = x_t + Tv_{f_t} cos(\theta_t + \frac{T}{2}\frac{v_f sin(\phi_t)}{L} + \phi_t) \\ y_{t+1} = y_t + Tv_{f_t} sin(\theta_t + \frac{T}{2}\frac{v_f sin(\phi_t)}{L} + \phi_t) \\ \theta_{t+1} = \theta_t + T\frac{v_f sin(\phi_t)}{L} \end{cases}$$

VII. Experiences

A. Tracking Results

The purpose of this experiment is to test the importance of the choice of the correct motion model to achieve more accurate tracking. It is intended to understand if a robust model of vehicle behavior modeling is relevant, depending on the frequency at which data is obtained and their accuracy. The basic idea is that the perception of a vehicle trajectory over time seen from a distant perspective is different from the analysis done locally.

This notion of observation distance is extrapolated to sampling frequency from the obtained sensing data.

The theory under test is that if we have few measurements of the position of a vehicle over time we do not need to know much about its dynamics to assess its trajectory. That is, if the data acquisition is very spaced in time, the sensitivity of the main characteristics that characterize the behavior of a vehicle, such as the impossibility of sliding laterally, is lost.

Therefore it would not be difficult to imagine that the behavior of the vehicle could be described by a simplistic motion model, such as a unicycle or, in the limit, by a random walk, constrained to the direction of the traffic circulation, as is often done in literature, to study properties of traffic for example.

However, since cars are moving at relatively high speeds in this type of infrastructure, it is not clear that a more robust motion model, such as the car model, produces significant improvements on tracking, comparatively with an unicycle model, for typical sampling frequencies of data acquisition.

The following is a study of the application of these motion models to an Extended Kalman Filter, for a range of sampling frequencies and for several degrees of noise of the vehicle's position measurements.

The motion models under study and comparison are the Random Walk, Car Model and Unicycle Model.

In order to compare the performance of the models in question, it is necessary to ensure that the filter is correctly calibrated. The proper choice of Extended Kalman Filter parameters ensures that the filter converges and significantly improves its performance. Calibrating the EKF is one of the biggest challenges in its use.

B. Dataset

The Dataset used for testing and calibration purposes, US Highway 101 Dataset, was obtained from the NGSIM website (www.ngsim.fhwa.dot.gov). The NGSIM datasets represent the most detailed and accurate field data collected for traffic micro simulation research and development. Data were collected through eight cameras placed on top of a 154-meter building, adjacent to the US-101 Hollywood Freeway in Los Angeles, California. The analyzed section is 640 m, 5 lanes in the South direction along with a one on-ramp and one off-ramp. This vehicle trajectory data provided the precise location of each vehicle every one-tenth of a second, resulting in detailed lane positions and locations relative to other vehicles. Because the NGSIM data records the position of every vehicle ten times per second, it can be treated as ground truth data. The data were collected on 15 June 2005 and record a total 45 minutes of data segmented in three contiguous time intervals:

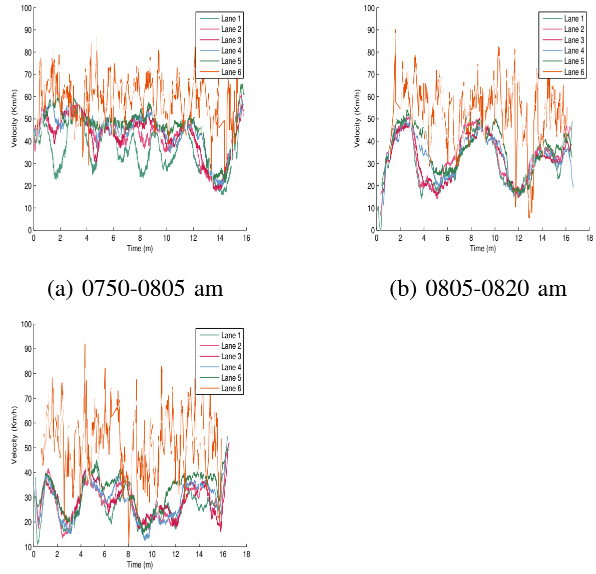
- 7:50 a.m. to 8:05 a.m.;
- 8:05 a.m. to 8:20 a.m.;
- 8:20 a.m. to 8:35 a.m.;

The datasets reflect clear whether, good visibility and dry pavement conditions.

These data originated the trajectories of 6101 vehicles: 5919 cars, 137 heavy vehicles an 45 motorcycles. The vehicle flow is 8077 vehicles per hour. It presents 18 characteristics for each instant of time, such as lateral and longitudinal position, instantaneous speed and acceleration, time, track number, vehicle class, previous and antecedent vehicle and etc.

The Dataset was standardized by converting the measures. Feet were converted to meters and milliseconds were converted to seconds. To use the data set in the EKF calibration and to obtain vehicle trajectories it is necessary to estimate three additional parameters: vehicle orientation, angular velocity and steering angle.

In 3 we can see the average instantaneous speed, by lane, over time. The right lanes have higher average speed values as was expected. The most left lane has higher flow of vehicles with higher velocities because is a HOV lane - "High Occupancy Vehicles" are lanes added to existing facilities reserved at peak travel times or longer for the exclusive use of vehicles with a driver and one or more passengers. The standard deviation is approximately 10 km / h.

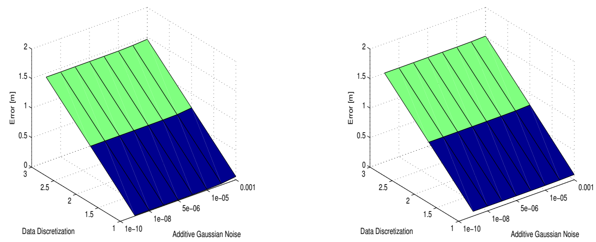


(a) 0750-0805 am

(b) 0805-0820 am

(c) 0820-0835 am

Figure 3: Instantaneous Average Velocity



(a) Car motion model

(b) Unicycle motion model

Figure 4: Tracking error computed based on Car and Unicycle motion models.

C. Comparison of motion models

After calibration of the filter for the car and unicycle motion models, we analyze the vehicle trajectory estimation error for several levels of discretization of the dataset and for different matrices of Gaussian noise covariance added to the initial trajectory. Discretization of data between 1 and 3 means that all Dataset points, half Dataset points, and one-third of Dataset points were used in consecutive experiments. That is, we are comparing sampling frequencies of 100, 200 and 300 ms. For each of these sampling frequencies, Gaussian noise was added with diagonal covariance matrices where the variance of X is set equal to the variance of Y. Eight noise levels were tested and their covariance assumes values between 1e-10 and 1e-3. In total, twenty four experiments were performed and the results are shown below.

As can be seen from the graphics **??** and **??**, the car model produces better vehicle tracking results than the unicycle.

The significant increases in both motion models result error, which can be found in figure 5, correspond to the increase in Dataset discretization what proves that by increasing the discretization of the dataset, both motion models have inferior

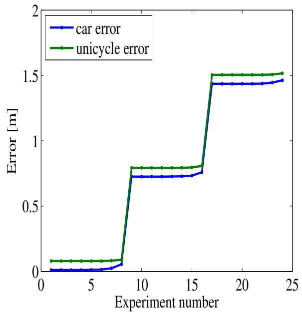


Figure 5: Tracking Error Result from Car and Unicycle Motion Model

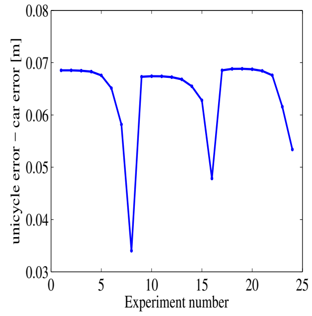


Figure 6: Difference between Tracking Error Result from Car and Unicycle Motion Model

performance.

Although the car model, for low levels of discretization tested, always produce better results than the unicycle model, the difference begins to dissipate as noise levels increase, for the same discretization level. The minimums observed in figure 6, which expresses the difference of the error between the results of unicycle and the car, clearly indicate that for the same level of discretization, when the measurements begin to become very noisy, the gain of using a more precise model, such as the car model, is diminished.

Through the graphics 7 which shows the relative difference of the error between the result of the two motion models, it becomes clear that with a high frequency of data acquisition, is an advantage to choose a more robust motion model. The car model produces a more precise vehicle tracking, in the order of

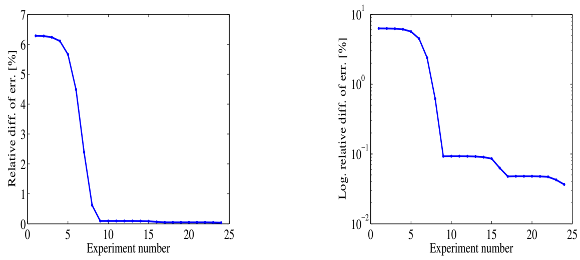


Figure 7: Difference between Tracking Error Result from Car and Unicycle Motion Model

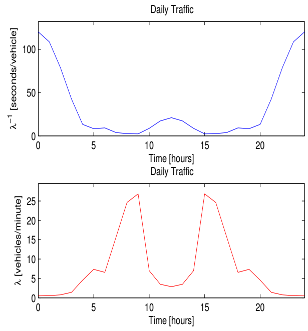


Figure 8: Profile of the daily traffic on the studied lanes

6.5 $\%$ better than the unicycle model, for the minimum time slot of obtaining data tested. The analysis of the presented graphics allows to conclude that the performance of the car model strongly decay with the increase of discretization and noise level so, for applications where high accuracy tracking is required, it is necessary to ensure that a robust motion model should be combined with a big data acquisition rate and a precise vehicle detection.

D. Illumination Results

In this section two global minimization algorithms of the illumination state vector will be compared. The configuration of the dimming level of the space luminaire set will be find while is intended to achieve a compromise between maximizing energy savings and ensuring the safety of road users.

Both algorithms, explained in detail in V, attempt to find the best lighting configuration at each instant of time to match the lighting requirements for all segments of the lane.

The experiment is carried out for a period of 24 hours and simulates two public roads: a tunnel and a bridge. The only difference between the two is that it is considered that during a time period coincident with the sun exposure, the bridge has all its luminaires turned off.

1) : Experience Setup

The work of [1] tests and discusses the best setup for the realization of the experience. The goal is to make a performance study of the two presented algorithms so was considered as presuppositions of the experiment, the parameters that the original dissertation proved to be the most adequate.

- It is assumed that the illumination of the space under study is obtained through LED luminaires because they meet the characteristics necessary to perform the experiment: dimming level capacity and linear behavior, ie, linear decay with distance. It is assumed that the illumination produced by each luminaire is equivalent to a triangular illumination window given by the expression 11 The lighting range, d_{rng}, is set equal to $3L$;
- The configuration of the test environment is 3.2km and the lamps are placed with $L = 80m$ from each other. It is therefore considered that there are $M = 40$ luminaires.
- Each vehicle is considered to require a triangular illumination window centered on the center of mass of the

vehicle, with a length equivalent to the positioning of five luminaires, ie 400 m. Whenever there are vehicles near, the windows of the various vehicles are merged into a single window that assumes the maximum value of the windows that gave rise to it as explained in detail in V

- The discretization of the bridge is $n = 40$, which implies a $\delta = 80m$ accordingly with 17. Thus the matrix A has dimension $[M, n] = [40, 40]$, the vector b has dimension $[1, n] = [40, 1]$ and the dimming level configuration vector to be obtained has dimension $[40, 1]$;
- The entrance of vehicles on the road has a random initial departure delay given by a Poisson distribution and the vehicles are considered moving at a constant velocity in the range [50, 120] km / h. In Figure 8 we can observe the distribution of traffic throughout the day for the experiences considered given by the Poisson distribution. The first graphic shows how many seconds takes, on average, the inter-arrival time between consecutive vehicles and the second graphic shows how many vehicles, on average, enter the bridge per minute.

The width of the lane was neglected in the application of the optimization by assuming that the lamps are placed 80 m from each other. Considering that the width of the roadway is approximately 10 % of that value and that a luminaire guarantees the necessary illumination to the area in which it is placed, vehicles traveling in any lane of the road are properly illuminated.

E. Experience Results

An evaluation and comparison of the performance of the algorithms previously detailed will be done here. Using the Matlab Linprog tool, the aforementioned algorithms were implemented and tested. For the purpose of comparison they will be called Algorithms 1 and 2, in which Algorithm 1 refers to the approach proposed by [1]. The simulation parameters, common to the test of both algorithms, are those mentioned in the previous subsection. As a performance evaluator of the algorithms, the Utilization Factor is used, which is given by the expression:

$$U = \frac{\sum_{t=0}^{T} \sum_{i=1}^{M} x_i(t)}{MT} \qquad (25)$$

This measurer allows an adequate comparison of the performance between the application to a tunnel and a bridge for normalizing the energy consumption in relation to the time of application.

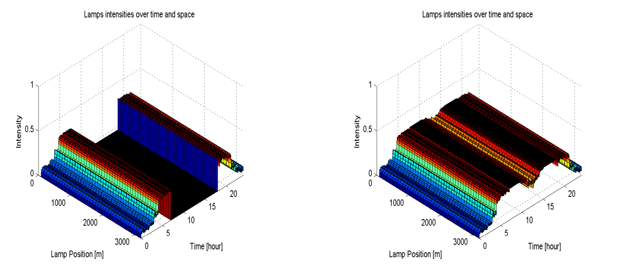
Algorithm 1

The first algorithm under test, Algorithm 1, aims to find the optimum dimming level vector of all the luminaires in the bridge. In the matrix form it is given by:

$$x^* = arg_x \, min \sum_{i=1}^{M} x_i \quad , i = 1, ...M \qquad (26)$$

$$s.to \begin{cases} Ax >= b \\ 0 \leq x_i \leq 1 \end{cases}$$

where the first constraint implies that the desired illumination levels, given by vector b, are reached or exceeded and the second one requires that the physical restrictions of the lamps are respected.



(a) Bridge (b) Tunnel

Figure 9: Bridge and tunnel illumination control using algorithm 1.

Figures 9a and 9b show the weighted average of the optimization result of the luminaires over 24 hours for the various bridge segments.

By analyzing the Utilization Factor for the experiment, it is clear that the implementation of the proposed algorithm would allow for considerable energy savings. For the tunnel the value of the utilization factor is approximately 78% while for the bridge it is approximately 63%. Achieving energy savings of 22% and 37% for tested configurations represents a very significant improvement over conventional systems.

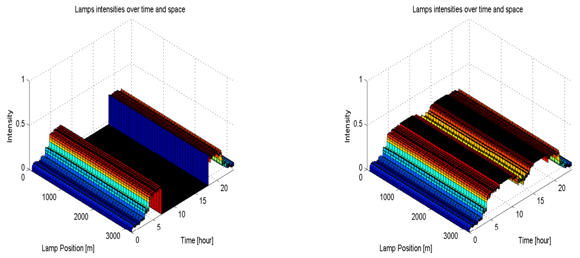
Algorithm 2 The alternative to the algorithm previously presented is based on the fact that the current rules for the illumination of public spaces do not require absolute values of illumination but rather means of illumination and limit of contrast. Intuitively, what is proposed with this variation of algorithm 1 is to ensure that the average illumination of continuous segments of the bridge is equal to the illumination required for areas considered occupied. It is also ensured that in addition to obtaining an average illumination, the absolute value of illumination can not be less than a certain percentage of the desired value. This allowed deviation was set at 30%. That is, it is intended to find the optimum state vector for all the luminaires of the bridge so that the average of subsequent zones that would be considered to be illuminated is equal to the absolute value that was required in the previous formulation and that the absolute value for each zone is at least 70% of the previous absolute value.

Formally the optimization problem, in the matrix form, is presented as

$$x^* = arg \, min \sum_{m=1}^{M} x(m)$$

$$s.to \begin{cases} \frac{1}{size_{R_j}} \sum_{(x_j, y_j) \in R_j} Ax \geq b, \quad j = 1, 2, ..., J \\ E_T(x_j, y_j) \geq (1 - C_o) L_o, \; \forall (x_j, y_j) \in R_j \; j = 1, 2, ..., J \\ 0 \leq x_i \leq 1, \; i = 1, ..., M \end{cases}$$

Regarding the formulation presented in the lighting chapter, this version does not account for the contribution of daylight and it is considered that no minimum level of illumination is required for unoccupied areas outside the lighting windows applied to vehicles. In figures 10a and 10b the average of the illumination values is presented for a simulation over 24h,



(a) Bridge (b) Tunnel

Figure 10: Bridge and tunnel illumination control using algorithm 2.

Algorithm	Tunnel UF [%] Lamps on 24h/day	Bridge UF [%] Lamps off 7:00 to 18:00
1	78.8	62.7
2	**72.0**	**55.9**

parameterized in the same way as the previous one. It is possible to see, by direct comparison of the images, that the illumination values obtained in this experiment are lower than the previous ones. Comparing the Utilization Factor, which for the algorithm 2 is approximately 72% for the Tunnel and 56% for the bridge, it is concluded that this approach allows to obtain more energy savings, with consequent monetary savings, compared to the previous approach. Specifically, it allows to improve approximately 28% in relation to the current systems and 7% in relation to the previous algorithm for the tunnel and 44% in relation to the current systems and 12% in relation to the previous algorithm for the Bridge.

This work presents the architecture of a system with the purpose of controlling the illumination of public roads, such as bridges and tunnels. Two subsystems of this global architecture were thoroughly covered: Vehicle Tracking and Lighting Optimization.

The main contribution in the Vehicle Tracking section is the result of the performance study of distinct Motion Models, used as a system model of an Extended Kalman Filter to perform vehicles tracking, which shows that the use of more robust models yelds gain when combined with a high frequency of sensing data acquisition.Is also presented the evidence that Tracking performance is linearly related to the frequency of obtaining sensor data and inversely related to the noise levels of the data.

The main contribution in the Illumination Optimization section is the comparison of two optimization algorithms, in which both produce promising results in relation to conventional lighting techniques. It is also proved that the introduction of a new approach to the optimization problem allows to achieve better results in the minimization of energy consumed while ensuring the safety of users and meets the standards required for this type of infrastructure.

There are however much space for improvements in the future.

As a continuation of the work carried out in the vehicles tracking the next step would be the study and implementation of a multi-target tracker. We have more than one target being tracked simultaneously so it becomes necessary associate the detection measures to the corresponding target - data association.

Following the study of lighting optimization problems, the next step would undoubtedly be the study of distributed lighting control algorithms. There are already some promising bases in the illumination of interior spaces that could be extrapolated to our reality of study, [3] and [12].

References

[1] R. Caetano. Adaptive illumination. 2014.

[2] D Caicedo, A Pandharipande, and G Leus. Occupancy-based illumination control of led lighting systems. *Lighting Research & Technology*, 43(2):217–234, 2011.

[3] David Caicedo and Ashish Pandharipande. illumination control with local sensing and actuation in networked lighting systems. *Sensors Journal, IEEE*, 13(3):1092–1104, 2013.

[4] Alessandro De Luca, Giuseppe Oriolo, and Claude Samson. Feedback control of a nonholonomic car-like robot. In *Robot motion planning and control*, pages 171–253. Springer, 1998.

[5] Igor Griva, Stephen G Nash, and Ariela Sofer. *Linear and nonlinear optimization*. Siam, 2009.

[6] Rudolph Emil Kalman et al. A new approach to linear filtering and prediction problems. *Journal of basic Engineering*, 82(1):35–45, 1960.

[7] Ashish Pandharipande and David Caicedo. Daylight integrated illumination control of led systems based on enhanced presence sensing. *Energy and Buildings*, 43(4):944–950, 2011.

[8] Ashish Pandharipande and David Caicedo. Adaptive illumination rendering in led lighting systems. *Systems, Man, and Cybernetics: Systems, IEEE Transactions on*, 43(5):1052–1062, 2013.

[9] Andrea Peruffo, Ashish Pandharipande, David Caicedo, and Luca Schenato. Lighting control with distributed wireless sensing and actuation for daylight and occupancy adaptation. *Energy and Buildings*, 97:13–20, 2015.

[10] Maria Isabel Ribeiro. Kalman and extended kalman filters: Concept, derivation and properties. *Institute for Systems and Robotics*, page 43, 2004.

[11] Gabriel A Terejanu. Extended kalman filter tutorial. *Online]. Disponible: http://users. ices. utexas. edu/˜ terejanu/files/tutorialEKF. pdf*, 2008.

[12] Haixu Wang, Ashish Pandharipande, David Caicedo, and PPJ van den Bosch. Distributed lighting control of locally intelligent luminaire systems. In *Systems, Man, and Cybernetics (SMC), 2012 IEEE International Conference on*, pages 3167–3172. IEEE, 2012.

[13] Hongming Yang and Ashish Pandharipande. Disaggregated daylight–artificial light sensing. *Sensors Journal, IEEE*, 12(12):3438–3445, 2012.