Novi pristup detekciji i praćenju prednjih svjetala vozila u noćnim uvjetima

Mentor:
Sven Lončarić

Darko Jurić

Sadržaj

- Problemi
- Postojeća rješenja i nedostaci
  - Detekcija svjetala
  - Grupiranje
  - Klasifikacija
  - Praćenje svjetala
- Novi pristup
  - Detekcija i klasifikacija objekata
  - Praćenje objekata
  - Demo

Problemi - sa strane implementacije

- Nemogućnost obuhvaćanja željenog raspona intenziteta:

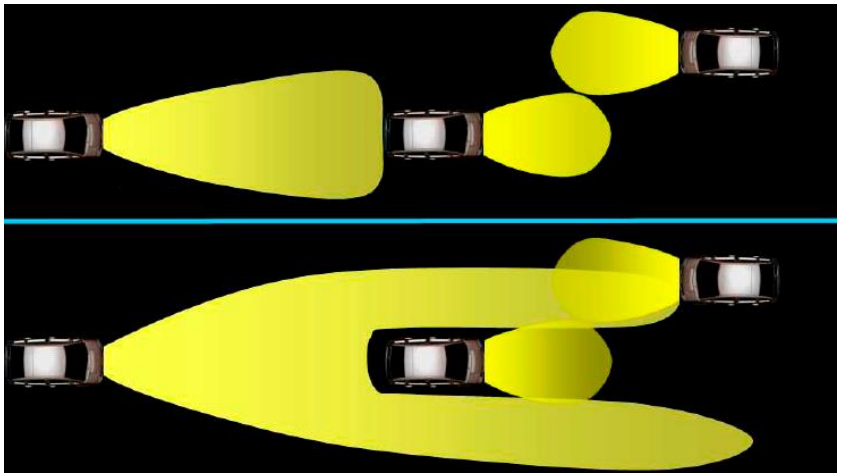
	Velika ekspozicija	Mala ekspozicija
Prednja svjetla – velika udaljenost	Dobra detekcija	Loša detekcija
Stražnja svjetla – mala udaljenost	Zasićenost	Dobra detekcija

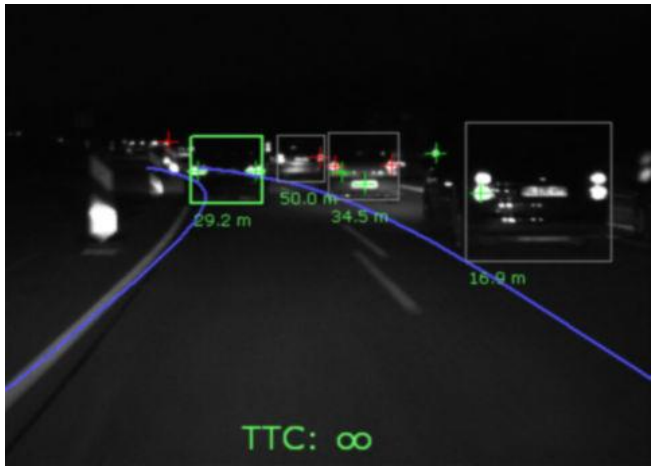
- Teško razlikovanje udaljenih svjetala (pojavljuju se kao jedan objekt)
- Postizanje robusnosti na vremenske uvjete
- Robusnost i brzina algoritama na ugradbenim računalima – rad u stvarnom vremenu

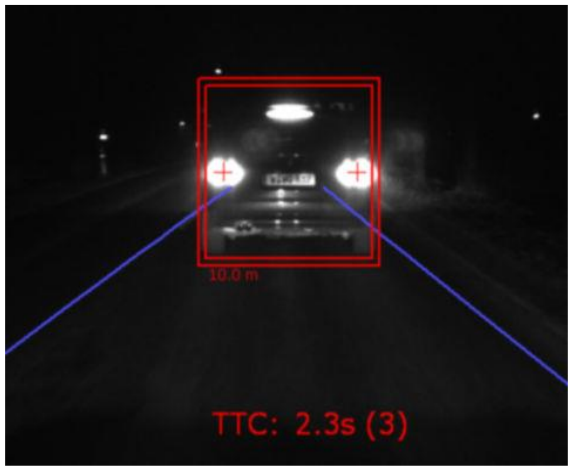
Postojeći sustavi

- Upravljanje dugim svjetlima
- Mjerenje udaljenosti
- Mjerenje brzine

Upozoravanje na koliziju



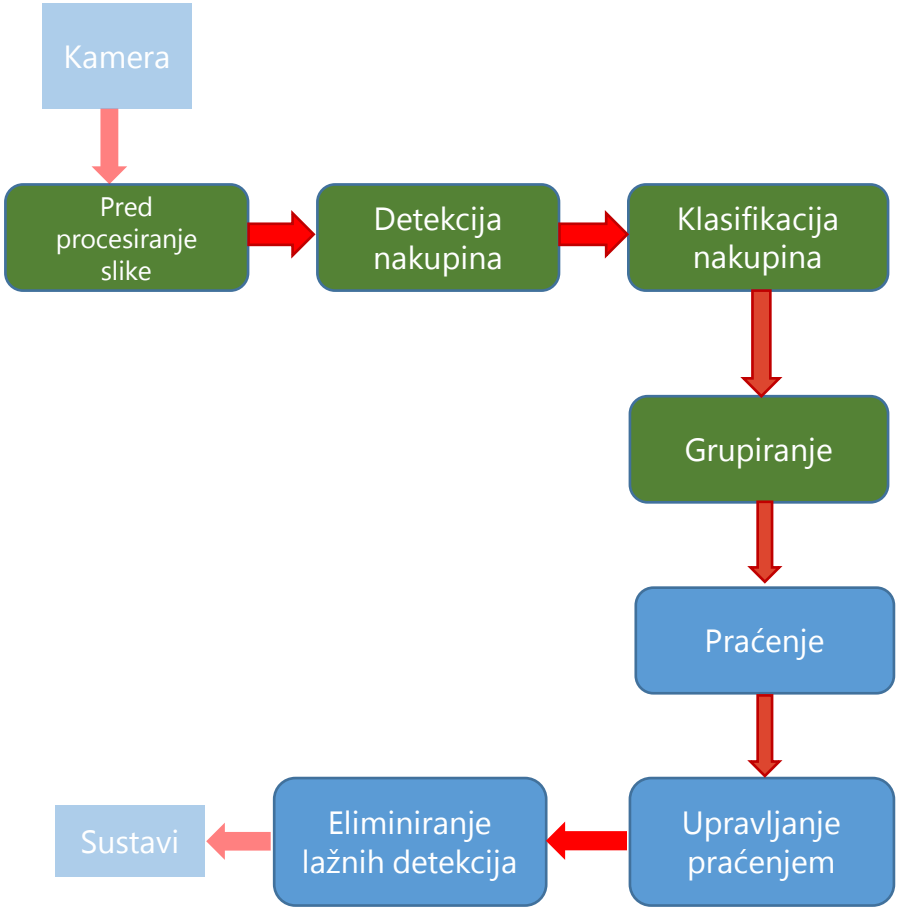




- Gormer S., Muller D., Hold S., Meuter M., Kummert A., Vehicle Recognition and TTC Estimation at Night based on Spotlight Pairing, *ntelligent Transportation Systems* , 2009
- Alcantarilla P.F., Begasa L.M.Jimenez P., Automatic LightBeam Controller for driver assistance, *Machine Vision and Applications* 22.5, 2011

Arhitektura

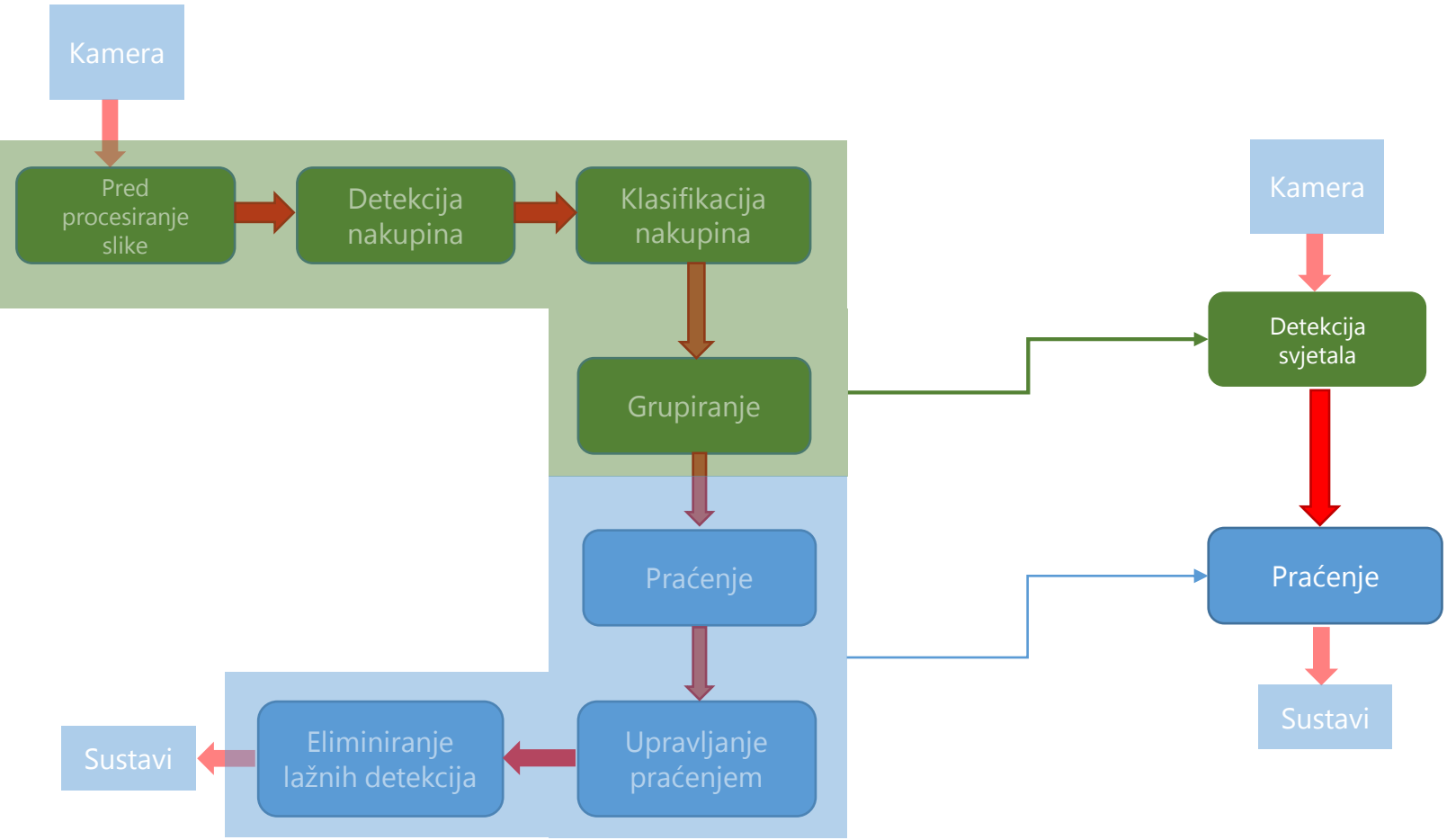
Uobičajena:



Arhitektura

Uobičajena:

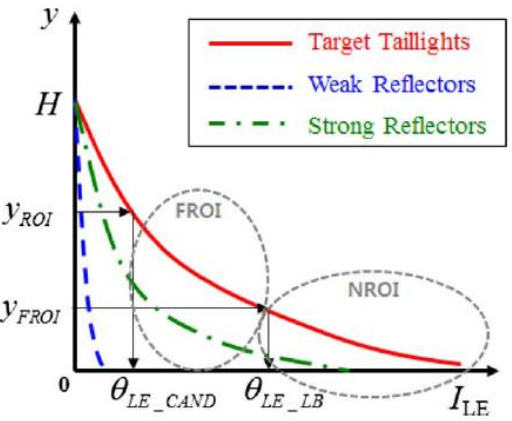
Nova:



Ekspozicija

Odabir ekspozicije

- Fiksna
- Automatska



- O' Malley, Jones E., Glavin M. Rear-Lamp Vehicle Detection and Tracking in Low- Exposure Video for Night Conditions, *Intelligent Transportation Systems, IEEE Transactions on* 11.2 , 2010
- Eum S., Jing H., Enhancing Light Blob Detection for Intelligent Headlight Control Using Lane Detection, *Intelligent Transportation Systems*, 2013

Ekspozicija

- Nedostaci fiksne ekspozicije:
  - Većina radova zahtjeva fiksnu ekspoziciju – nemogućnost rada drugih sustava
  - Kompenzacija između količine osvijetljenosti i dobrog prikaza objekta – usko područje uporabe

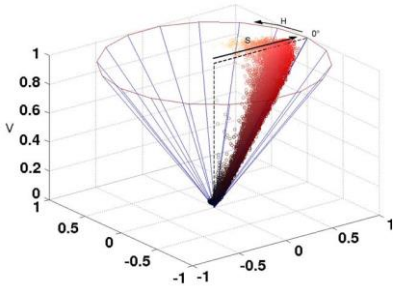
Postojeći sustavi - Detekcija svjetala vozila

- Slike u različitim prostorima boja (HSV, Crvena + Mono, Mono slika)
- Pragovi:
  - Fiksni (binarni, donja granica…)
  - Adaptivni (fiksna vrijednost + adaptivna devijacija, Otsu bazirane)
- Druge metode:
  - LoG (i aproksimacije)
  - Širenje regija

- Li Y., Haas N., Pankanti S., Intelligent Headlight Control Using Learning-based Approaches, *Intelligent Vehicles Symposium (IV)* , 2011
- Chen Y., Chaing H.H., A Vision-Based Driver Nighttime Assistance and Surveillance System Based on Intelligent Image Sensing Techniques and a Heterogamous Dual-Core Embedded System Architecture, *Sensors* 12.3 , 2012
- Ogura R., Ohashi G., Vehicles Detection Based on Extremas in Nighttime Driving Scene, *Consumer Electronics (GCCE),* 2012

Postojeći sustavi - Detekcija svjetala vozila - pragovi

- Fiksni pragovi: detekcija stražnjih svjetala
  - Skupljanje uzoraka
  - HSV prostor
  - pragovi



- Fiksni + adaptivni pragovi: detekcija svjetala
  - Automatska ekspozicija – stražnja udaljena
  - Niska ekspozicija – bliska & udaljena

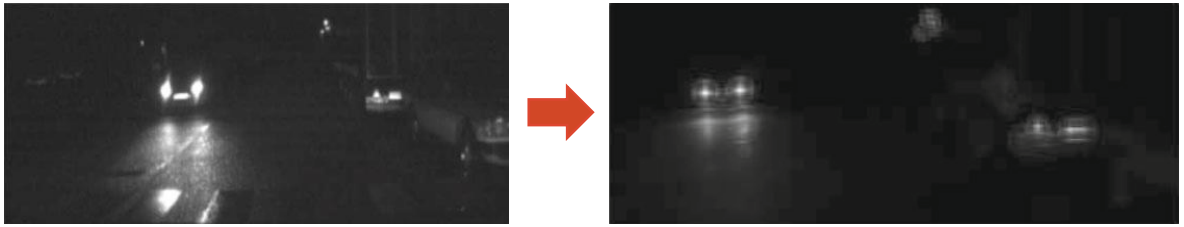
- O' Malley, Jones E., Glavin M. Rear-Lamp Vehicle Detection and Tracking in Low- Exposure Video for Night Conditions, *Intelligent Transportation Systems,* 2010
- Alcantarilla P.F., Begasa L.M., Jimenez P., Automatic LightBeam Controller for driver assistance, *Machine Vision and Applications* 22.5 , 2011
- Eum S., Jing H., Enhancing Light Blob Detection for Intelligent Headlight Control Using Lane Detection, *Intelligent Transportation Systems*, 2013

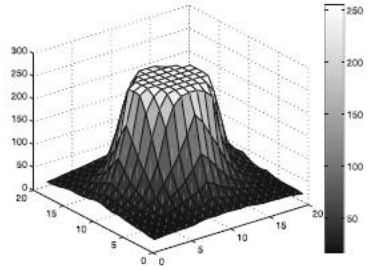
Postojeći sustavi - Detekcija svjetala vozila -pragovi

- Nedostaci:
  - Podrazumijeva se fiksna ekspozicija kamere kao i drugih parametara
  - Ograničena uporaba kamere od strane drugih aplikacija
  - Postavljanje pragova ne uzima u obzir strukturu objekta
  - Fiksni pragovi se ne mogu prilagoditi drugačijim okolinama
  - Fiksni + adaptivni prag (*Alcantarilla et al.*) uzima u obzir dvije slijedne slike – ne podržavaju svi uređaji

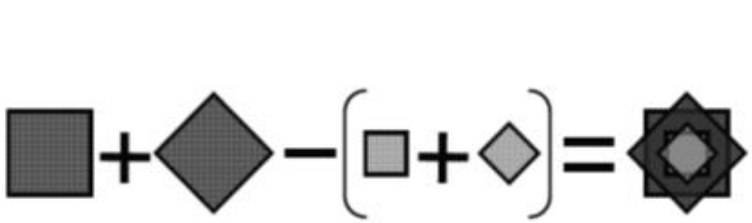
Postojeći sustavi - Detekcija svjetala vozila - LoG

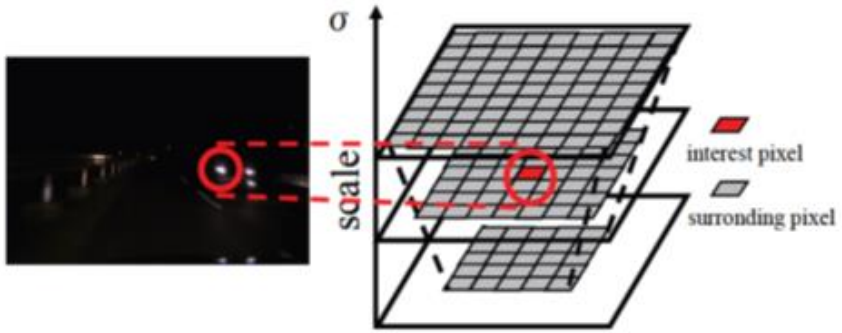
- LoG i aproksimacija: detekcija svjetala
  - Normalizirani Laplace operator $\nabla^2 L(x, y, \sigma) = \sigma^2 \cdot (L_{xx} + L_{yy})$





  - Aproksimacija Laplaceovog operatora - CenSurE





- Alcantarilla P.F., Begasa L.M.Jimenez P., Automatic LightBeam Controller for driver assistance, *Machine Vision and Applications* 22.5 , 2011
- Ogura R., Ohashi G., Vehciles Detection Based on Extremas in Nighttime Driving Scene, *Consumer Electronics (GCCE)* , 2012

Postojeći sustavi - Detekcija svjetala vozila - LoG

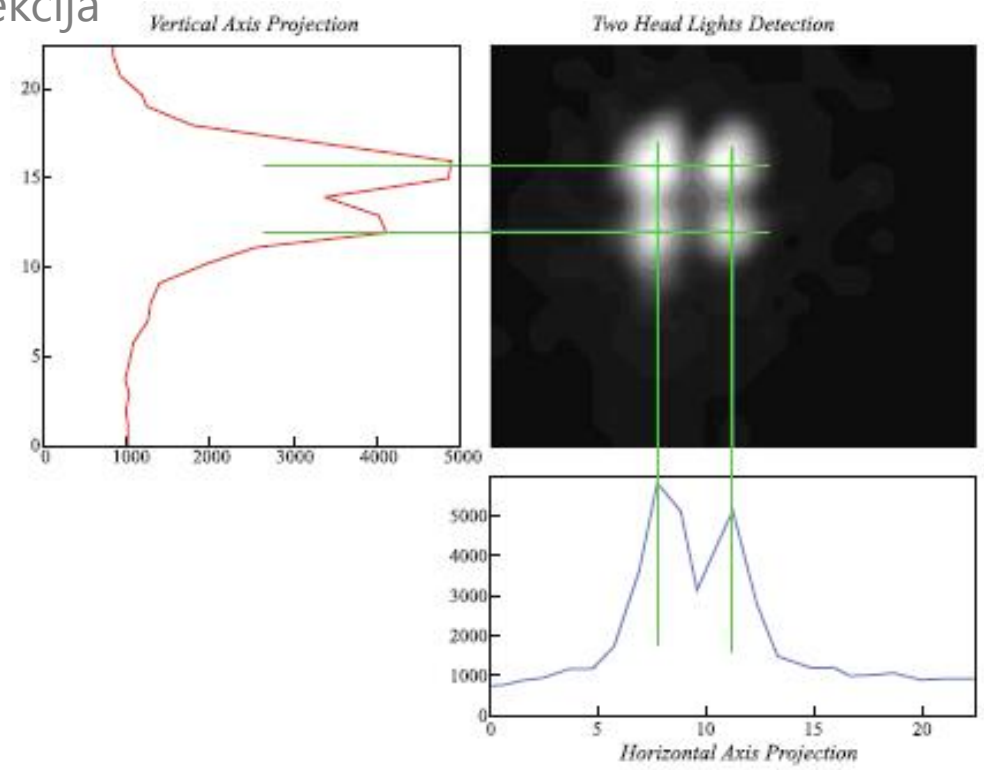
- Nedostaci:
  - Mora se načiniti više prolazaka kroz sliku (različite skale)
  - Skupa operacija – osobito ako se ne rabe aproksimacije
  - Dobar odziv na strukture kružnog oblika – ne mora biti zadovoljeno za bliža prednja svjetla, a osobito ne za stražnja svjetla

Postojeći sustavi - Detekcija svjetala vozila – refleksija ceste

- Rješavanje refleksije svjetla o cestu* (dijeljenje nakupine)

  1. horizontalna i vertikalna projekcija

  2. Podizanje praga



- Fossati A., Schonmann P. Fua P., Real-Time Tracking for Driving Assistance, *Machine Vision and Application*, 2011
- Alcantarilla P.F., Begasa L.M.Jimenez P., Automatic LightBeam Controller for driver assistance, *Machine Vision and Applications* 22.5 , 2011

Postojeći sustavi - Detekcija svjetala vozila – refleksija ceste

- Nedostaci

  1. razrješavanje refleksija samo uz pomoć pragova je neadekvatno – ne uzima se u obzir struktura – lažne detekcije

  2. Uzimanjem vertikalne i horizontalne projekcije se podrazumijeva broj modova za pojedine objekte – ovisno o pragu

Postojeći sustavi - Grupiranje svjetala

Većina radova: grupiranje prije klasifikacije

Tehnike:

kros-korelacija

križanje kovarijanci

sličnost boja, veličina, pozicija

kombinacije…

Normalizirane mjere za računanje vjerojatnosti – izbjegavanje više pragova

- Eum S., Jung H., Enhancing Light Blob Detection for Intelligent Headlight Control using Lane Detection, *Intelligent Transportation Systems*, 2012
- O' Malley, Jones E., Glavin M. Rear-Lamp Vehicle Detection and Tracking in Low- Exposure Video for Night Conditions, *Intelligent Transportation Systems,* 2010
- Chen Y., Lin C., Fan C., Vision based Nighttime Vehicle Detection and Range Estimation for Driver Assistance, *Systems, Man and Cybernetics,* 2008
- Fossati A., Schonmann P. Fua P., Real-Time Tracking for Driving Assistance, *Machine Vision and Applications,* 2011

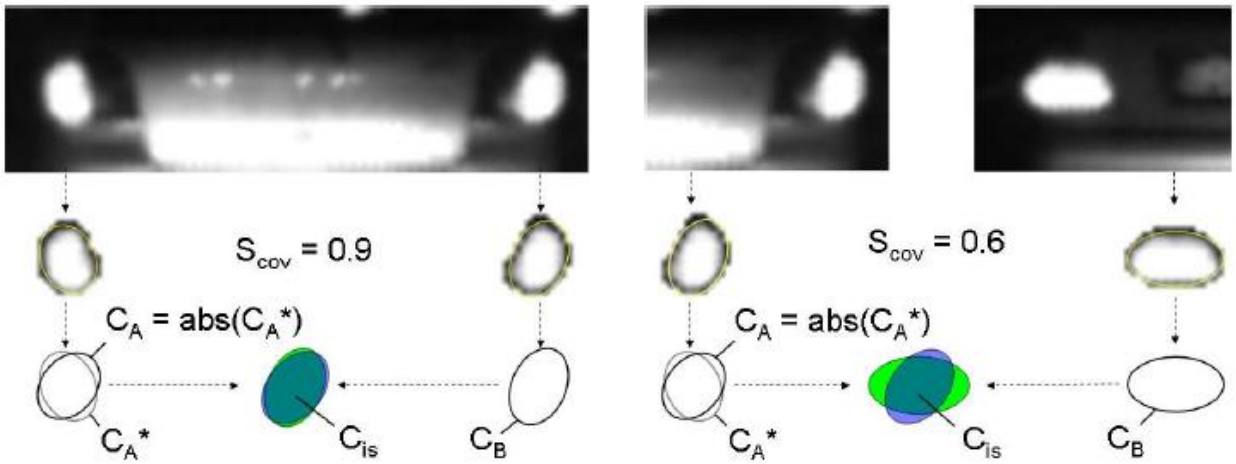
Postojeći sustavi - Grupiranje svjetala: križanje matrica 2 reda

Matrica momenata 2 reda:

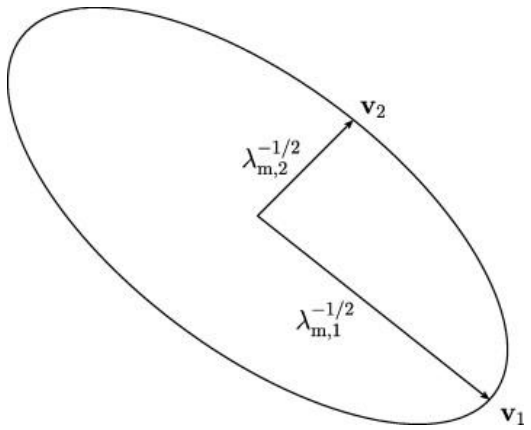
$$C_{X_1X_2} = \left| \frac{1}{M_{00}} \begin{bmatrix} \sum_x \sum_y (x-\mu_X)(x-\mu_x)w(x,y) & \sum_x \sum_y (x-\mu_X)(y-\mu_y)w(x,y) \\ \sum_x \sum_y (x-\mu_X)(y-\mu_y)w(x,y) & \sum_x \sum_y (y-\mu_y)(y-\mu_y)w(x,y) \end{bmatrix} \right|$$

Križanje matrica:

$$S_{COV} = \frac{\det(C_{IS})}{\max(\det(C_A).\det(C_B))}$$



PCA – određivanje veličine nakupine:



- Gormer S., Muller D., Hold S., Meuter M., Kummert A., Vehicle Recognition and TTC Estimation at Night based on Spotlight Pairing, *Intelligent Transportation Systems* , 2009

Postojeći sustavi - Grupiranje svjetala: križanje matrica 2 reda

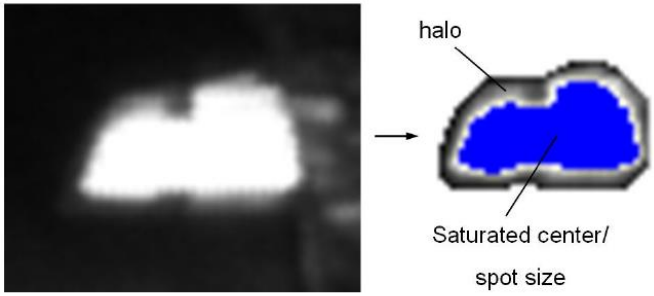
- Nedostaci

  1. provodi se na binariziranoj slici – ovisi o rezultatu predprocesiranja (pragovi, LoG)
  2. Nedovoljna značajka za uparivanje nakupina (svjetla su preslična)
  3. Svjetla su nepravilnog oblika – postavljanje elipse može uzrokovati veliku pogrešku

Postojeći sustavi - Grupiranje svjetala: omjer svjetlosnog pojasa / veličina svjetla

Mjera:

$$S_{COV} = \frac{\min(H_A, H_B)}{\max(H_A, H_B)}$$



Halo obruč – „Black hat" transformacija: *BH_T = morfološko zatvaranje (slika) - slika*

- Gormer S., Muller D., Hold S., Meuter M., Kummert A., Vehicle Recognition and TTC Estimation at Night based on Spotlight Pairing , *Intelligent Transportation Systems* , 2009
- Alcantarilla P.F., Begasa L.M.Jimenez P., Automatic LightBeam Controller for driver assistance, *Machine Vision and Applications* 22.5 , 2011

Postojeći sustavi - Grupiranje svjetala: omjer svjetlosnog pojasa / veličina svjetla

- Nedostaci

  1. ovisi o ekspoziciji
  2. Primjenjivo u ruralnim područjima (ne urbanim)
  3. Primjenjivo za duga svjetla (ostala svjetla manji efekt)

Postojeći sustavi - Klasifikacija svjetala

- Korišteni klasifikatori
  - Pravila i granice, SVM, AdaBoost
- Značajke
  - Značajke **pozicije**: x, y (promet u različiti smjerovima, ulična svjetla različite koordinate)
  - Značajke **intenziteta**: srednja vrijednost i varijanca (prednja svjetla imaju veći intenzitet nego stražnja)
  - Značajke **oblika**: površina, BB / površina svjetla, kut, *veličina svjetlosnoga obruča (eng. halo)*, „halo" / površina zasićene regije
  - Značajke **oblika među uparenim nakupinama**
  - Značajke **boje**: HS(V) (prednja, stražnja i ostala svjetla nemaju istu boju)
  - Značajke **kretanja**: vektor kretanja (prednja svjetla prema, stražnja od, ostala prema rubovima)

- Li Y., Haas N, Pankanti S., Intelligent Headlight Control Using Learning-based approaches, *Intelligent Vehicles Symposium (IV)* , 2011
- Fossati A., Schonmann P., Fua P., Real-Time Vehicle Tracking for Driving Assistance, *Machine Vision and Applications* 22.2, 2011
- Chen Y., Chaing H.H., A Vision-Based Driver Nighttime Assistance and Surveillance System Based on Intelligent Image Sensing Techniques and a Heterogamous Dual-Core Embedded System Architecture, *Sensors* 12.3, 2012

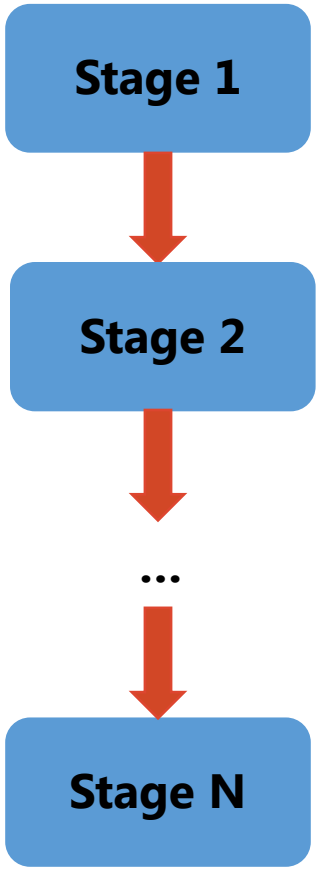
Postojeći sustavi - Klasifikacija svjetala

- Nedostaci

  1. izračunavanje značajki ovisi o ekstrakciji svjetlosnih nakupina
  2. Izračunavanje značajki – performanse
  3. Korišteni klasifikatori – velik broj objekata - performanse

Detekcija - novi pristup!

Detekcija



Stage - *Gentle boost*

Weak learner -*Regression tree*

Feature – *Pixel compairision*

$$\text{bintest}(I; \mathbf{l}_1, \mathbf{l}_2) = \begin{cases} 0, & I(\mathbf{l}_1) \leq I(\mathbf{l}_2) \\ 1, & \text{otherwise}, \end{cases}$$

- Markuš, Nenad, et al. "A method for object detection based on pixel intensity comparisons organized in decision trees." (2013).

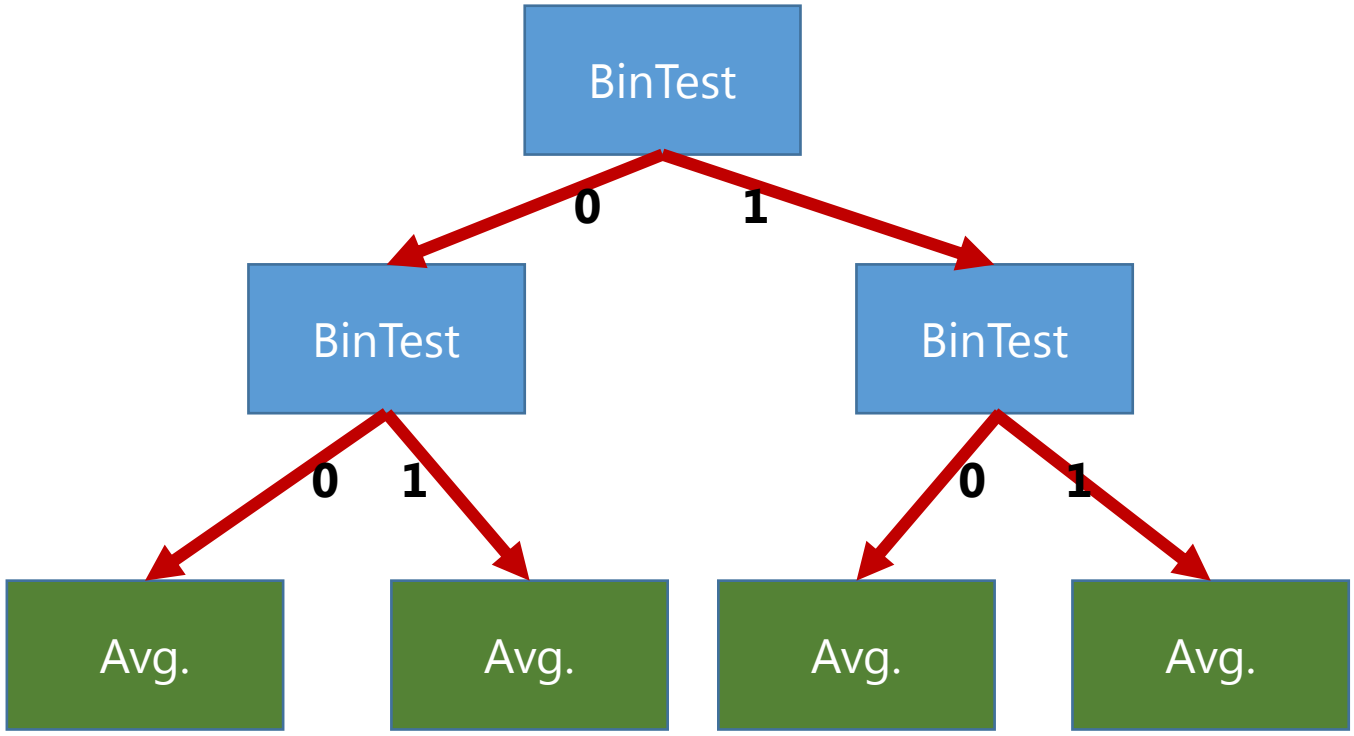
Detekcja

Gentle AdaBoost

1. Start with weights $w_i = 1/N$, $i = 1, 2, \ldots, N$, $F(x) = 0$.
2. Repeat for $m = 1, 2, \ldots, M$:
   (a) Fit the regression function $f_m(x)$ by weighted least-squares of y_i to x_i with weights w_i.
   (b) Update $F(x) \leftarrow F(x) + f_m(x)$.
   (c) Update $w_i \leftarrow w_i \exp(-y_i f_m(x_i))$ and renormalize.
3. Output the classifier $\text{sign}[F(x)] = \text{sign}[\sum_{m=1}^{M} f_m(x)]$.

- Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. "Special invited paper. additive logistic regression: A statistical view of boosting." *Annals of statistics*(2000): 337-374.

Detekcija



- Markuš, Nenad, et al. "A method for object detection based on pixel intensity comparisons organized in decision trees." (2013).

Detekcija

Testiranje...

$$\text{bintest}(I; \mathbf{l}_1, \mathbf{l}_2) = \begin{cases} 0, & I(\mathbf{l}_1) \leq I(\mathbf{l}_2) \\ 1, & \text{otherwise}, \end{cases}$$

$$\text{bintest}(\mathrm{I}; \mathrm{l}_1, \mathrm{l}_2, \mathrm{c}_1\mathrm{c}_2) = \begin{cases} 0, I(l_1, c_1) \leq I(l_2, c_2) \\ 1, \qquad\qquad otherwise \end{cases}$$

Postojeći sustavi - Praćenje svjetala

- Pretraživanje ograničene regije
- Kalman filter (stanje: x, y, duljina, širina)
- Pravila
  - Update,
  - Appear,
  - Merge,
  - Split

- Ne uzima u obzir model gibanja
- Sam ne nudi rješenje praćenja više objekata
- Posebno obrađene situacije koje su česte u praćenju

- Li Y., Haas N, Pankanti S., Intelligent Headlight Control Using Learning-based approaches, *Intelligent Vehicles Symposium (IV)* , 2011
- Fossati A., Schonmann P., Fua P., Real-Time Vehicle Tracking for Driving Assistance, *Machine Vision and Applications* 22.2 , 2011
- Chen Y., Chaing H.H., A Vision-Based Driver Nighttime Assistance and Surveillance System Based on Intelligent Image Sensing Techniques and a Heterogamous Dual-Core Embedded System Architecture, *Sensors* 12.3, 2012

Postojeći sustavi - Praćenje svjetala

- Autoregresija → Ne uzima u obzir procesni šum
- Prostorno vremenska slika + HMM → Parametri (14)
- Čestični filtar → broj čestica ograničava broj filtara
  - Asocijacija objekata - „hard gating"
- Vremenska usklađenost (eng. temoral coherence analysis) → Ne može točno locairati objekt
  - Ne nudi upravljanje praćenja

- A. L´opez, J. Hilgenstock, A. Busse, R. Baldrich, F. Lumbreras, and J. Serrat, "Nighttime vehicle detection for intelligent headlight control," in Advanced Concepts for Intelligent Vision Systems. Springer, 2008, pp. 113–124.
- C. Idler, R. Schweiger, D. Paulus, M. Mahlisch, and W. Ritter, "Realtime vision based multi-target-tracking with particle filters in automotive applications," in Intelligent Vehicles Symposium, 2006 IEEE. IEEE, 2006, pp. 188–193.
- J. Wang, X. Sun, and J. Guo, "A region tracking-based vehicle detection algorithm in nighttime traffic scenes," Sensors, vol. 13, no. 12, pp. 16 474–16 493, 2013.
- J. H. Connell, B. W. Herta, S. Pankanti, H. Hess, and S. Pliefke, "A fast and robust intelligent headlight controller for vehicles," in Intelligent Vehicles Symposium (IV), 2011 IEEE. IEEE, 2011, pp. 703–708.

Praćenje - novi pristup!

Praćenje- Joint Probability Data Association Filter (JPDAF)

Track managment – *JPDAF + Entropy based tracking managment*

Multi-object tracking – JPDAF

Tracker – *Extended Kalman filter*

$$J = \begin{bmatrix} \frac{\partial F_1}{\partial x_1} & \cdots & \frac{\partial F_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial F_m}{\partial x_1} & \cdots & \frac{\partial F_m}{\partial x_n} \end{bmatrix}.$$

State:

$S = [x \quad y \quad d \quad v]$

Measurement:

$M = [x \quad y \quad d]$

Praćenje - Joint Probability Data Association Filter (JPDAF)

Problem asocijacije detekcije i trake

$$\beta = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1m} \\ \vdots & \ddots & \vdots \\ \beta_{n1} & \cdots & \beta_{nm} \end{bmatrix}$$

mjerenja

trake

Za svaku traku (algoritam praćenja)

Za svaku detekciju

1) izračunaj udaljenost mjerenja od trake

2) izračunaj gating – ovisno o algoritmu

ako je gating zadovoljavajući

3) izračunati $P(z_j|x_i)$

- Juric-Kavelj, Srecko, Ivan Markovic, and Ivan Petrovic. "People Tracking with Heterogeneous Sensors using JPDAF with Entropy Based Track Management."*Proceedings of the 5th European Conference on Mobile Robots (ECMR2011)*. 2011.

Praćenje - Joint Probability Data Association Filter (JPDAF)

- Izračunavanje faktora pripadnosti detekcije i trake

$$P\left(\mathbf{z}_j^{s_k} \left| \theta_h(k) \right.\right) = \begin{cases} P_F^{s_k}, & \mathbf{z}_j^{s_k} \text{ false alarm} \\ P_D^{s_k} P\left(\mathbf{z}_j^{s_k} \left| \hat{\mathbf{x}}_t^k \right.\right), & \mathbf{z}_j^{s_k} \text{ existing track} \end{cases}$$

$$\beta_j^t = \frac{1}{c} \sum_{\theta \in \Theta_{jt}^k} \prod_{j=1}^{m_k} P\left(\mathbf{z}_j^{s_k} \left| \theta \right.\right)$$

- Pridjeljivanje novih detekcija trakama

  Pridijeliti novu taku ukoliko mjerenje nije pridruženo niti jednoj traci (redak u β matrici)

- Rješavanje nevaljanih traka i lažnih detekcija)

  Zapamtiti početnu entropiju (ovisno o algoritmu praćenja)
  Ukoliko se entropija poveća za X (50%) uništiti traku
  Ukoliko se entropija smanji za Y (20%) tada se uzima kao pouzdana

- Juric-Kavelj, Srecko, Ivan Markovic, and Ivan Petrovic. "People Tracking with Heterogeneous Sensors using JPDAF with Entropy Based Track Management."*Proceedings of the 5th European Conference on Mobile Robots (ECMR2011)*. 2011.

Praćenje – JPDAF - Kalman

Weighted innovation:

$$\nu^t = \sum_{j=1}^{m_k} \beta_j^t \nu_j^t \qquad \nu_j^t = \mathbf{z}_j^{s_k} - \mathbf{H}\hat{\mathbf{x}}_t^{k-}$$

Gating:

$$\nu_j^{t\,T} \mathbf{S}_t^{-1} \nu_j^t$$

Update:

$$\beta^t = 1 - \sum_{j=1}^{m_k} \beta_j^t$$

$$\hat{\mathbf{x}}_t^k = \hat{\mathbf{x}}_t^{k-} + \mathbf{K}_k \nu^t$$

$$\mathbf{P}_t^k = \beta^t \mathbf{P}_t^{k-} + (1-\beta^t)\left[\mathbf{I} - \mathbf{K}_k \mathbf{H}\right] \mathbf{P}_t^{k-} + \mathbf{K}_k \mathbf{P}_{\nu^t} \mathbf{K}_k^T$$

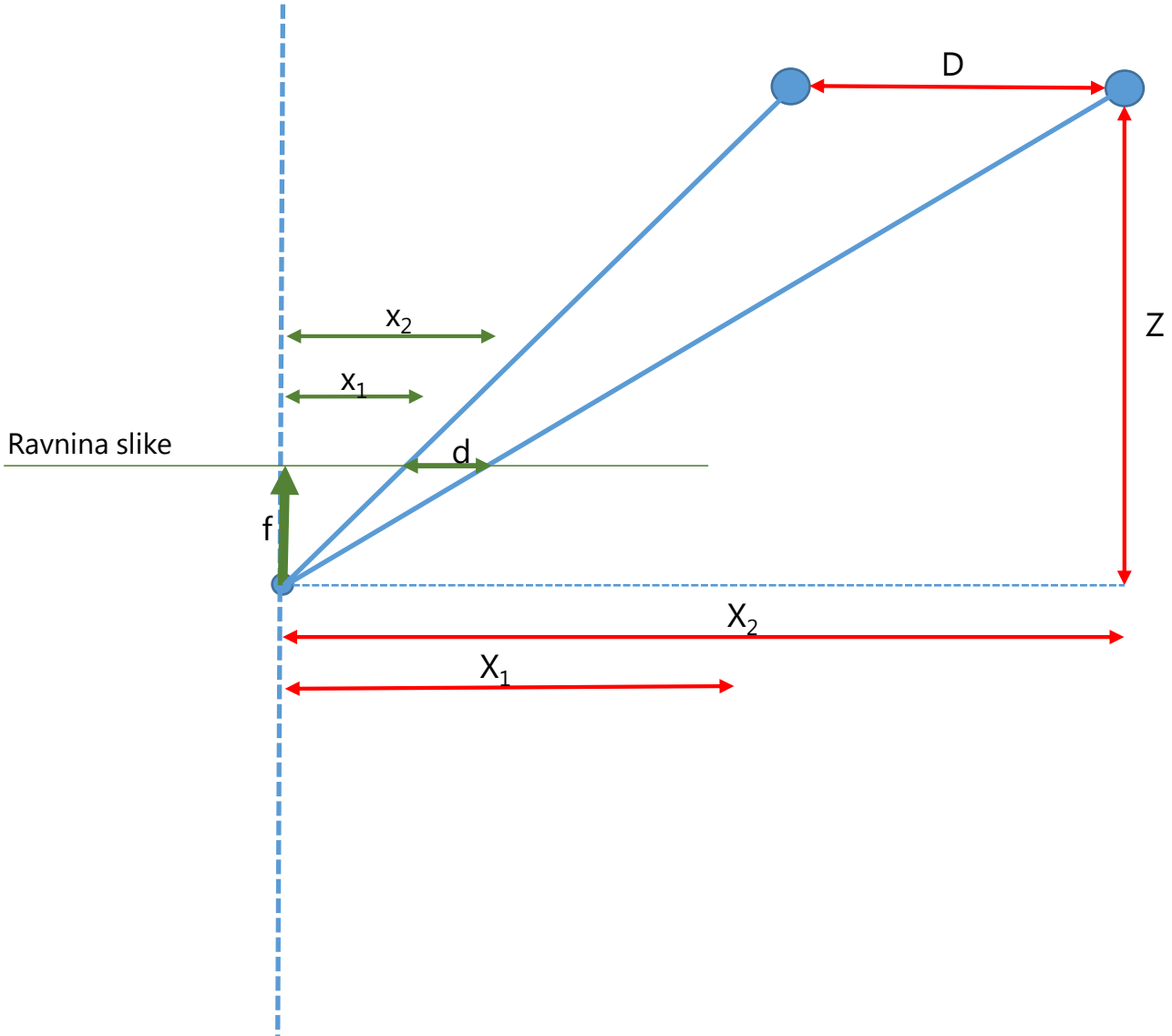
Računanje entropije:

Dimenzionalnost stanja

$$H_2(\hat{\mathbf{x}}_t) = -\log \int p\left(\hat{\mathbf{x}}_t\right)^2 d\hat{\mathbf{x}}_t \quad \Rightarrow \quad H_2(\hat{\mathbf{x}}_t) = \frac{n}{2} \log 4\pi + \frac{1}{2} \log \left|\mathbf{P}_t\right|$$

- Juric-Kavelj, Srecko, Ivan Markovic, and Ivan Petrovic. "People Tracking with Heterogeneous Sensors using JPDAF with Entropy Based Track Management."*Proceedings of the 5th European Conference on Mobile Robots (ECMR2011)*. 2011.

Praćenje - model

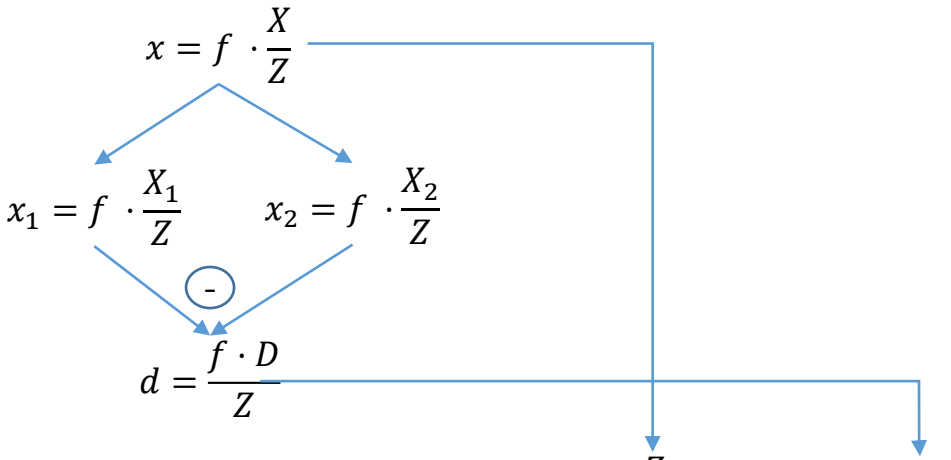


$$S = [x \quad y \quad d \quad v]$$

$$x(t+1) = f\big(x(t)\big) = ?$$

$$y(t+1) = f\big(y(t)\big) = ?$$

$$v(t+1) = f\big(v(t)\big) = ?$$



$$x + \Delta x = \mathrm{f} \cdot \frac{X}{Z + \Delta Z} = f \cdot \frac{X}{Z + v \cdot \Delta t} = f \cdot \frac{\frac{Z}{f}}{Z + v \cdot \Delta t} \cdot x = \frac{f \cdot \frac{D}{d}}{f \cdot \frac{D}{d} + v \cdot \Delta t} \cdot x = \frac{f \cdot D}{f \cdot D + v \cdot \mathrm{d} \cdot \Delta t} \cdot x \Rightarrow$$

$$\Rightarrow \boldsymbol{x(k)} = \frac{f \cdot D}{f \cdot D + v(k-1) \cdot d(k-1) \cdot \Delta t} \cdot x(k-1)$$

Visina svjetala (analogno):

$$\boldsymbol{y(k)} = \frac{f \cdot D}{f \cdot D + v(k-1) \cdot d(k-1) \cdot \Delta t} \cdot y(k-1)$$

Razmak između svjetala:

$$(x_2 + \Delta x_2) - (x_1 + \Delta x_1) = d + \Delta d = \frac{f \cdot D}{f \cdot D + v \cdot \mathrm{d} \cdot \Delta t} \cdot x_2 - \frac{f \cdot D}{f \cdot D + v \cdot \mathrm{d} \cdot \Delta t} \cdot x_1 = \frac{f \cdot D}{f \cdot D + v \cdot \mathrm{d} \cdot \Delta t} \cdot d$$

$$\Rightarrow \boldsymbol{d(k)} = \frac{f \cdot D}{f \cdot D + v(k-1) \cdot d(k-1) \cdot \Delta t} \cdot d(k-1)$$

Brzina:

$$\frac{d + \Delta d}{d} = \frac{f \cdot D}{f \cdot D + v \cdot d \cdot \Delta t} \Rightarrow \quad v = f \cdot D \cdot \frac{d - d + \Delta d}{d \cdot (d + \Delta d) \cdot \Delta t} \Rightarrow \quad \boldsymbol{v(k-1)} = f \cdot D \cdot \frac{d(k-2) - d(k-1)}{d(k-2) \cdot d(k-1) \cdot \Delta t}$$

Demo

Demo

Pitanja ?