



Itasdi

Innovative Teaching Approaches in development of Software
Designed Instrumentation and its application in real-time
systems

Theory of Robotics Systems

Localization – Kalman Filter

Co-funded by the
Erasmus+ Programme
of the European Union





Innovative Teaching Approaches in development of Software Designed Instrumentation and its application in real-time systems

Faculty of Technical
Sciences



Ss. Cyril and Methodius
University
Faculty of Electrical Engineering
and Information Technologies



Zagreb University of
Applied Sciences



School of Electrical
Engineering
University of Belgrade



Faculty of Physics
Warsaw University of Technology



Co-funded by the
Erasmus+ Programme
of the European Union





Itasdi

Innovative Teaching Approaches in development of Software
Designed Instrumentation and its application in real-time
systems

Teorija Robotskih Sistema

Localizacija

Co-funded by the
Erasmus+ Programme
of the European Union





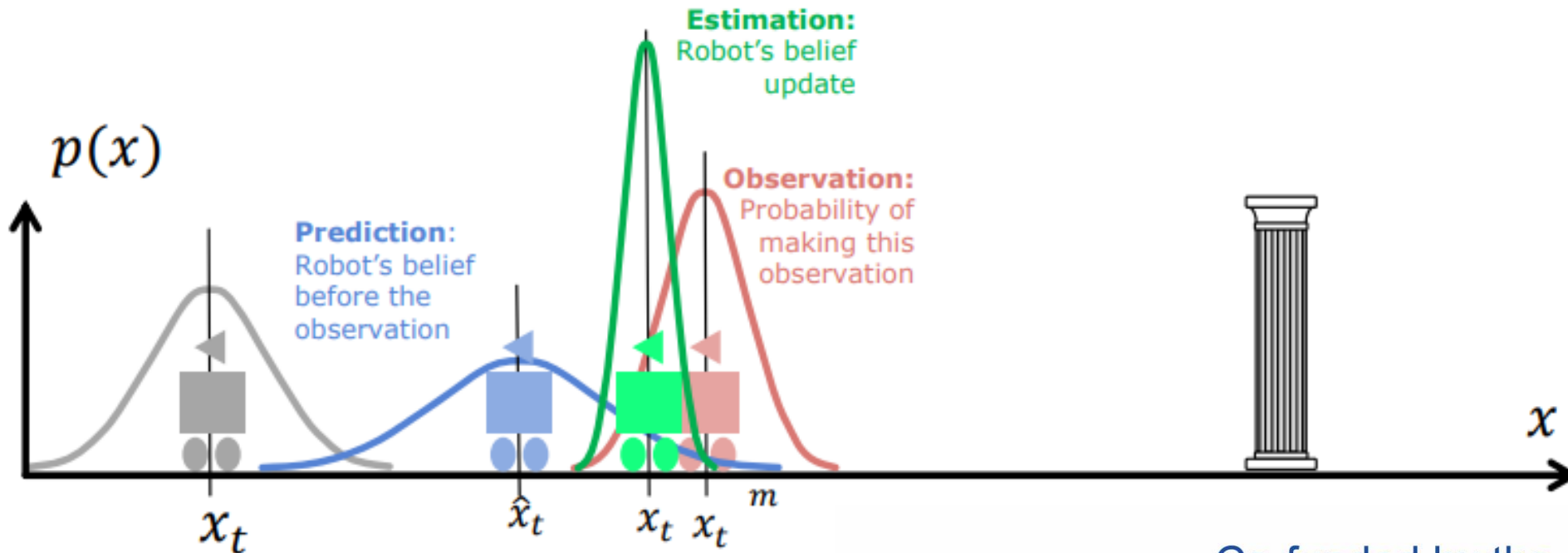
Loklazacija Kalmanovim filtrom (ukratko)

1. **Predikcija (ACT)** zasniva se na prethodnoj proceni i odometriji.
2. **Opservacija (SEE)** koristeći postojeće senzore na robotu.
3. **Predikcija merenja** zasnovana na predikciji i mapi.
4. **Uparivanje** opserviranih obeležja i mape.
5. **Estimacija** → Popravka pozicije (posteriorna pozicija)





Loklazacija Kalmanovim filtrom (ukratko)





Kalmanov filter – teorija

- Sistem je linearan i model šuma može biti predstavljen kao Gausovski.
- Tokom faze **predikcije** i **opservacije** u celom sistemu se menjaju samo parametri Gausove raspodele (μ_t, Σ_t) .
- Zasniva se na 4 jednačine:
 - 2 za estimaciju (μ_t, Σ_t) u fazi **predikcije**.
 - 2 za popravku (μ_t, Σ_t) u fazi **opservacije**.
- Koristi teoremu o totalnoj verovatnoći i Bajesovo pravilo.





Kalmanov filter – Teorema o totalnoj verovatnoći

- Posmatramo dve nezavisne slučajne promenljive x_1 i x_2 koje normalno raspoređene.
- $x_1 = N(\mu_1, \sigma_1^2)$, $x_2 = N(\mu_2, \sigma_2^2)$
- Postoji funkcija $y = f(x_1, x_2)$ - f linearna funkcija $y = Ax_1 + Bx_2$
- Kako će biti raspodeljeno y ? $\langle y \rangle = A\mu_1 + B\mu_2$; $\sigma_y^2 = A^2\sigma_1^2 + B^2\sigma_2^2$
- U slušaju vektora: $\langle y \rangle = A\mu_1 + B\mu_2$; $\Sigma_y = A\Sigma_1^2A^T + B\Sigma_2^2B^T$





Kalmanov filter – Teorema o totalnoj verovatnoći

- Šta ako f nije linearna funkcija? y nije normalno raspoređeno
- Linearizacije prvog reda: $y \cong f(\mu_1, \mu_2) + F_{x_1}(x_1 - \mu_1) + F_{x_2}(x_2 - \mu_2)$
- F_{x_1} i F_{x_2} predstavljaju Jakobijane od f
- $\langle y \rangle = y \cong f(\mu_1, \mu_2);$
- $\Sigma_y = F_{x_1} \Sigma_1^2 F_{x_1}^T + F_{x_2} \Sigma_2^2 F_{x_2}^T$

} Predikcija za EKF





Kalmanov filter – Bajesovo pravilo

- Pozicija robota q , verovatnoća da se robot nalazi na toj poziciji $p_1(q)$ i verovatnoća da se robot nalazi na toj poziciji prema eksteroceptivnim senzorima $p_2(q)$.
- $p_1(q) = N(\hat{q}_1, \sigma_1^2)$; $p_2(q) = N(\hat{q}_2, \sigma_2^2)$
- Finalna raspodela $p(q)$ će biti proporcionalna proizvodu $p_1(q) \cdot p_2(q)$

$$\frac{1}{\sigma_1 \sqrt{2\pi}} \exp\left(-\frac{(q - \hat{q}_1)^2}{2\sigma_1^2}\right) \cdot \frac{1}{\sigma_2 \sqrt{2\pi}} \exp\left(-\frac{(q - \hat{q}_2)^2}{2\sigma_2^2}\right) = \frac{1}{\sigma_1 \sigma_2 2\pi} \exp\left(-\frac{(q - \hat{q}_1)^2}{2\sigma_1^2} - \frac{(q - \hat{q}_2)^2}{2\sigma_2^2}\right)$$



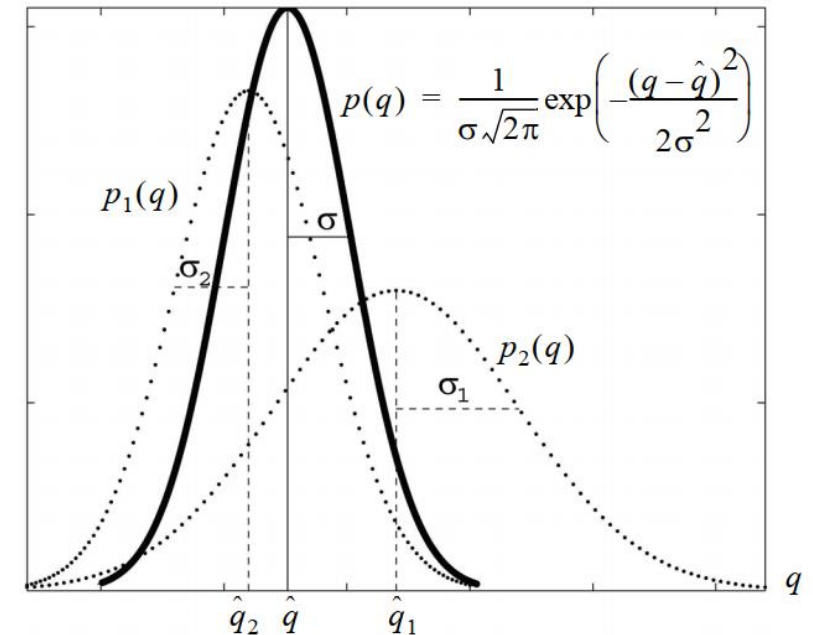


Kalmanov filter – Bajesovo pravilo

$$\frac{1}{\sigma_1\sqrt{2\pi}} \exp\left(-\frac{(q-\hat{q}_1)^2}{2\sigma_1^2}\right) \cdot \frac{1}{\sigma_2\sqrt{2\pi}} \exp\left(-\frac{(q-\hat{q}_2)^2}{2\sigma_2^2}\right) =$$

$$\frac{1}{\sigma_1\sigma_2 2\pi} \exp\left(-\frac{(q-\hat{q}_1)^2}{2\sigma_1^2} - \frac{(q-\hat{q}_2)^2}{2\sigma_2^2}\right) = \Omega \exp\left(-\frac{(q-\hat{q})^2}{2\sigma^2}\right)$$

$$\hat{q} = \hat{q}_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} (\hat{q}_2 - \hat{q}_1) \quad \sigma^2 = \sigma_1^2 - \frac{\sigma_1^4}{\sigma_1^2 + \sigma_2^2}$$





Kalmanov filter

- Ukoliko je u pitanju više-dimenziona slučajna promenljiva
- $\hat{q} = q_1 + P(P + R)^{-1}(q_2 - q_1)$
- $\hat{P} = P - P(P + R)^{-1}P$
- Gde su P i R kovarijacione matrice slučajnih promenljivih q_1 i q_2
- $K = P(P + R)^{-1}$ Kalmanovo pojačanje
- Inovacija - $q_2 - q_1$; Kovarijaciona matrica inovacije - $\Sigma_{IN} = P + R$





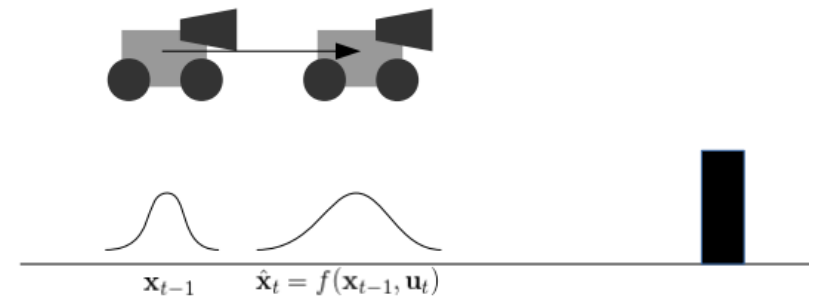
Primena Kalmanovog filter na AMR

- Predikcija:

- Pozicija x_t u trenutku t zavisi od pozicije u prethodnom trenutku x_{t-1} i kretanja robota koje se desi nakon upravljačkog signala u_t .

- $\hat{x}_t = f(x_{t-1}, u_t); P_t = F_x P_{t-1} F_x^T + F_u Q_t F_u^T$

- $Q_t = \begin{bmatrix} k|\Delta s_l| & 0 \\ 0 & k|\Delta s_r| \end{bmatrix}$

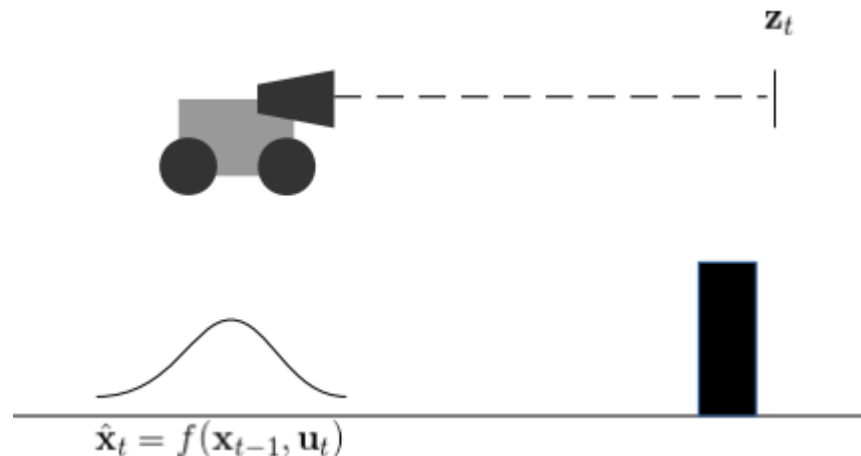




Primena Kalmanovog filterar na AMR

- **Opservacija:**

- Merenja senzora z_t u trenutku t . U opštem slučaju postoji n merenja z_n^i ($i = 1 \dots n$)
- Transformacija obeležja mape u lokalni koordinatni sistem se vrši funkcijom h .

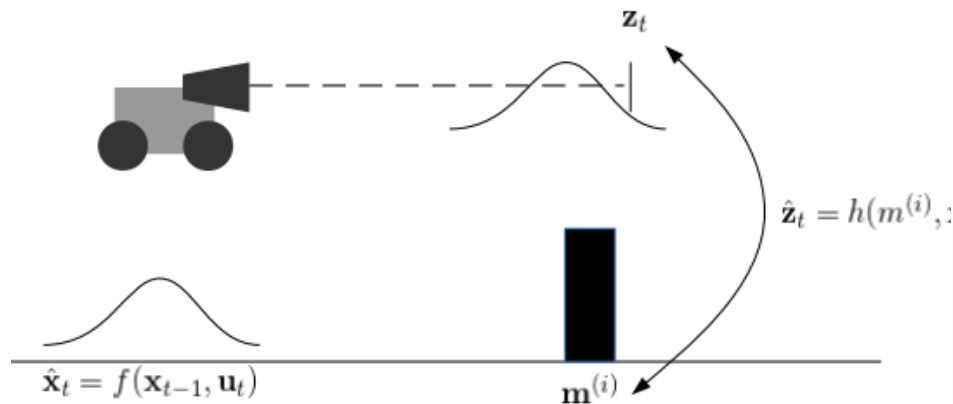




Primena Kalmanovog filtera na AMR

• Predikcija merenja:

- Predviđena pozicija robota $\hat{\mathbf{x}}_t$ i obeležja mape M koristimo za predviđanje merenja z_t^j
- $\hat{z}_t^j = h^j(\hat{\mathbf{x}}_t, m^j)$
- $m^j = [\alpha^i \quad r^i]^T$ - jedno obeležje mape



$$\mathbf{H} = \begin{bmatrix} \frac{\partial h_1}{\partial x} & \frac{\partial h_1}{\partial y} & \frac{\partial h_1}{\partial \theta} \\ \frac{\partial h_2}{\partial x} & \frac{\partial h_2}{\partial y} & \frac{\partial h_2}{\partial \theta} \end{bmatrix} =$$

$$\begin{bmatrix} 0 & 0 & -1 \\ -\cos(W\alpha^j) & -\sin(W\alpha^j) & 0 \end{bmatrix}$$





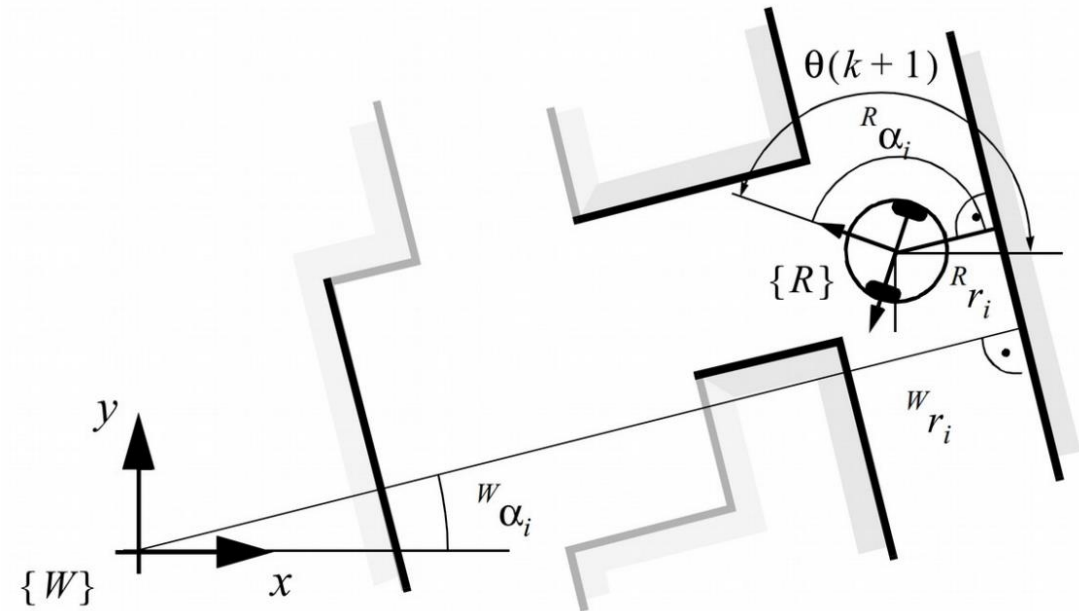
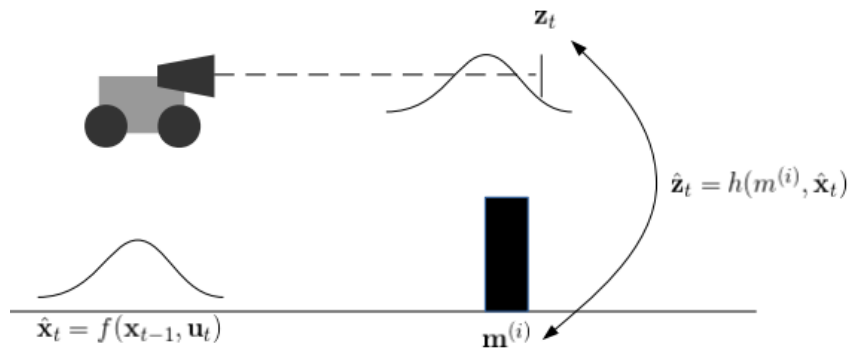
Primena Kalmanovog filterar na AMR

- Predikcija merenja:

- $m^j = [\alpha^i \quad r^i]^T$ - jedno obeležje mape

- $\hat{z}_t^j = \begin{bmatrix} R \hat{\alpha}^j \\ R \hat{r}^j \end{bmatrix} = h^j(\hat{x}_t, m^j) =$

- $\begin{bmatrix} W \alpha^j - \hat{\theta}_t \\ W r^j - (\hat{x}_t \cos(W \alpha^j) + \hat{y}_t \sin(W \alpha^j)) \end{bmatrix}$





Primena Kalmanovog filter na AMR

• Uparivanje:

- Za uparivanje koristimo razliku između svih merenja i mape.
- Ovakve razlike nazivamo *inovacijama*

$$\bullet v_t^{ij} = z_t^j - \hat{z}_t^i \quad \leftarrow \text{Predikcija merenja}$$

↑ ↙
Inovacija Opservacija

$$\bullet \sum_{IN_t}^{ij} = \hat{H}_t^i \hat{P}_t (\hat{H}_t^i)^T + R_t^j \quad \leftarrow \text{Kovarijansa merenja}$$

↑
Kovarijansa inovacije





Primena Kalmanovog filter na AMR

- Uparivanje:

- Da bi za obeležje sa mape mogli da uparimo sa opserviranim obeležjem mora biti zadovoljen određeni uslov.
- Najčešće se koristi Mahalonobisova distanca
- $d_t^{ij} = (v_t^{ij})^T (\Sigma_{IN_t}^{ij})^{-1} v_t^{ij}$
- $d_t^{ij} < g^2$ - validaciona granica





Primena Kalmanovog filter na AMR

- Estimacija:

- Kada imamo predikciju i kada smo izvršili uparivanje obeležja primenjujemo Bajesovo pravilo.
- $x_t = \hat{x}_t + K_t v_t$
- $K_t = \hat{P}_t \hat{H}_t^T (\Sigma_{IN_t})^{-1}$
- $P_t = \hat{P}_t - K_t \Sigma_{IN_t} K_t^T$

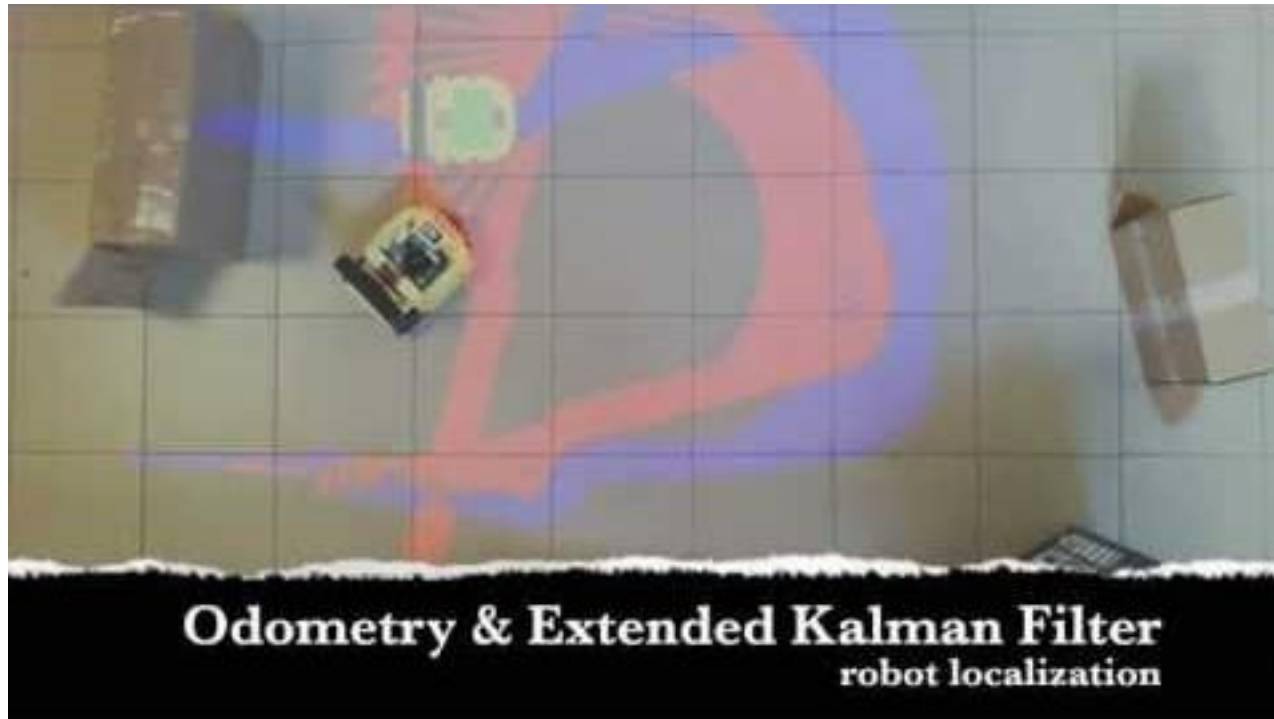




Innovative Teaching Approaches in development of Software Designed Instrumentation and its application in real-time systems

Itasdi

Primena Kalmanovog filtera na AMR



<https://www.youtube.com/watch?v=TnCouG221uo>

Co-funded by the
Erasmus+ Programme
of the European Union





Itasdi

Innovative Teaching Approaches in development of Software Designed Instrumentation and its application in real-time systems

Thanks!

Co-funded by the
Erasmus+ Programme
of the European Union

