# 확장칼만필터를이용한위치기반로봇시각제어 <br> Position-Based Robot Visual Servoing with Extended Kalman Filter for Pose Estimation <br> *찬민덕 ${ }^{1}$, 강희준 ${ }^{2}$ <br> *M. D. Tran ${ }^{1}$, ${ }^{\text {H }}$ H. J. Kang(hjkang@ulsan.ac.kr) ${ }^{2}$ <br> ${ }^{1}$ 울산대학교 전기공학부대학원, ${ }^{2}$ 울산대학교 전기공학부 

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## 1. INTRODUCTION

In visual servoing applications, two main approaches were defined: position based control and image based control. This article focuses on position based control. In this approach,the task function approachesare defined in terms of the Pose transformation (position and orientation) between the current and desired camera frame ${ }_{c^{*}}^{c} T$.

Many approaches have been proposed to estimate the 3D relative position and orientation using a single image view. The common approaches are based on two methods. The first methoduses task specific image preprocessing to extract the image featurelocation measurements. They are thencombined with known object CAD descriptions to estimate the Pose of the object with respect to camera frame. Then, estimated Pose can be composed with the object of desired Pose transformation to find the relationship between the current and the desired Pose for effective dynamic tracking control. The second method, the Kalman filter uses these measurements for the implicit solution of the photogrammetric equation and filtering of the resulting motion parameters to give optimal Pose estimation for real-time tracking control.However, these methods still have some limitationssuch as the effect of noise measurement, intrinsic camera parameters,...

This paper investigates the approach of estimating 3D motion parameters for tracking control. In this approach, an end-point mounted camera and image preprocessor system provide image plane measurements of selected known task object features.To reduce the bias of the Pose estimation, the extendedKalman filter is developed.The proposed system relies on the vision to generate relative Pose information. AKalman filter is then used to smooth the calculation and alsoincrease the robustness of the

## Pose estimation.

## 2. Position Based Visual Servoing with Extended Kalman Filter

The state estimation is based on a discrete-time none-linear state-space description of the head pose.

$$
\begin{align*}
& x(k+1)=f[x(k)]+w(k)  \tag{1}\\
& y(k)=h[x(k)]+v(k)
\end{align*}
$$

The state is composed of position and orientation. Position is described with Cartesian position $\mathrm{p}(\mathrm{k})$. The orientation is represented with quaternion $\mathrm{q}(\mathrm{k})$.

The dynamic equation of position is

$$
\begin{equation*}
p(k+1)=p(k)+\Delta T v(k)+w(k) \tag{2}
\end{equation*}
$$

where

$$
v(k)=\frac{p(k)-p(k-1)}{\Delta T}
$$

For quaternion

$$
\begin{equation*}
\dot{q}=\frac{1}{2} q \times \Omega \tag{3}
\end{equation*}
$$

$$
\begin{aligned}
& q(k+1)=\left(I+\frac{3}{4} \Omega_{k} \Delta T-\frac{1}{4} \Omega_{k-1} \Delta-\frac{1}{6}\left\|\omega_{\mathrm{k}}\right\|_{2}^{2} \Delta T^{2}\right. \\
&-\frac{1}{24} \Omega_{k} \Omega_{k-1} \Delta T^{2} \\
&\left.-\frac{1}{48}\left\|\omega_{k}\right\|_{2}^{2} \Omega_{k} \Delta T^{3}\right) q_{k}
\end{aligned}
$$

Where

$$
\Omega=\left[\begin{array}{cccc}
0 & -\omega_{x} & -\omega_{y} & -\omega_{z} \\
\omega_{x} & 0 & \omega_{z} & -\omega_{y} \\
\omega_{y} & -\omega_{z} & 0 & \omega_{x} \\
\omega_{z} & \omega_{y} & -\omega_{x} & 0
\end{array}\right]
$$



Fig 1:Position-based visual servoing with extended Kalman filter for pose estimation

The output vector is formed with position
$p_{m}(k)$ and quaternion $q_{m}(k)$ measurements from vision system

$$
H=\left[\begin{array}{ll}
I_{3 \times 3} & 0_{3 \times 4}  \tag{4}\\
0_{4 \times 3} & I_{4 \times 4}
\end{array}\right]
$$

The $w$ and $v$ denote the process noise and image parameter measurement noise that are assumed to be described by zero-mean Gaussian distribution with covariance $Q$ and $R$.

The recursive EKF algorithm consists of two major parts of prediction and estimation as follows.

Prediction:

$$
\begin{align*}
& \hat{x}_{k}^{-}=A \hat{x}_{k-1}  \tag{5}\\
& P_{k}^{-}=A P_{k-1} A^{T}+Q \tag{6}
\end{align*}
$$

Kalman gain update:

$$
\begin{equation*}
K_{k}=P_{k}^{-} H_{T}\left(R+H P_{k}^{-} H^{T}\right)^{-1} \tag{7}
\end{equation*}
$$

Estimation update:

$$
\begin{align*}
& \hat{x}_{k}=\hat{x}_{k}^{-}+K_{k}\left(z_{k}-h\left(\hat{x}_{k}^{-}\right)\right)  \tag{8}\\
& P_{k}=P_{k}^{-}-K_{k} H_{k} P_{k}^{-} \tag{9}
\end{align*}
$$

## Control Laws

The PBVS (position based visual servoing) scheme can be designed by using $s=\left({ }_{o}^{c} t,{ }_{o}^{c} \Theta\right)$, $s^{*}=0, e=s$. In this case the interaction matrix related to e is given by

$$
\dot{e}=\dot{s}=\left[\begin{array}{c}
{ }^{c}{ }_{c} \dot{t}  \tag{10}\\
{ }_{c}^{c *} \dot{{ }_{c}}
\end{array}\right]=\left[\begin{array}{cc}
{ }^{c}{ }_{c}^{*} R & 0 \\
0 & T^{-1}{ }_{c}^{*} R
\end{array}\right]\left[\begin{array}{c}
v_{c} \\
\omega_{c}
\end{array}\right]
$$

Where T is the matrix relationship between angle set velocity with the angular velocity of the camera.

$$
T(\Theta)=\left[\begin{array}{ccc}
0 & -\sin \varphi & \cos \varphi \cos \theta  \tag{11}\\
0 & \cos \varphi & \sin \varphi \cos \theta \\
1 & 0 & -\sin \theta
\end{array}\right]
$$

Follow exponential control method $\dot{e}=-\lambda e$, the required control command is expressed as

$$
{ }^{c} v_{c}=-\lambda\left[\begin{array}{cc}
\left({ }^{c}{ }_{c}^{*} R\right)^{T} \cdot{ }^{c *} t & o \\
o & \left({ }_{c}^{c *} R\right)^{T} \cdot T\left({ }_{c}^{c *} \Theta\right) \cdot{ }_{c}{ }_{c}^{c *} \Theta
\end{array}\right]
$$

## 3. SIMULATION RESULTS

Based on the previous description, a PBVS simulator is developed in matlab 2010a.In this simulation, object is fixed and four landmarks are set up in the same plane. The current camera Pose and design camera Pose are:
${ }_{o}^{c} P=\left([0 ; 0 ; 3],\left[0 ; \frac{\pi}{4} ; \frac{\pi}{6}\right]\right) ;{ }_{o}^{c *} P=([0 ; 0 ; 1.5],[0 ; 0 ; 0])$
The Fig. 2a shows the resultant trajectories of 4 landmarks in the image plane. The Fig. 2b shows a good converging of feature parameters error. It helpsto prove the control quality of improved PBVS algorithm. The Fig. 3a and 3b show the velocity plot
for both cases of conventional and extendedKalman


Fig 2: Convergence of visual feature error in PBVS


Fig 3: a) Velocity plot in conventional PBVS, b)
Velocity plot in extended Kalman filter PBVS

## 4. CONCLUSION

This paper showsthe position-based visual servoing. The application of the extended Kalman filter is used to reduce noise in image measurements. The Kalmanfilter makes the control smoothly and increases the robustness of the pose estimation. This simulation is useful in visual servoing area because the control less depends on the intrinsic camera parameters and extrinsic environment.

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