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# Robust control by adaptive Non-singular Terminal Sliding Mode

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ABSTRACT

Based on the principles of the Non-singular Terminal Sliding Mode Control (NTSMC), a new control law along with an Unscented Kalman Filter (UKF) has been proposed for robotic manipulators, that can tolerate external disturbances and noises with unknown statistics. First, a neural network module has been used as a discontinuous control part of the NTSMC to enhance the performance of the controller due to chattering phenomenon. Furthermore, a new methodology is proposed which is based on a modified evolutionary algorithm (charged systems search) to estimate the system states by the UKF and the measurement and process noise covariances. To compare this evolutionary method with classical methods, an optimal Unscented Kalman Filter (UKF) algorithm has been introduced that estimates the noise statistics recursively within the algorithm. The proposed control method and observer have been simulated on a 6-DOF robot manipulator.

## 1. Introduction

Motion control has become one of the most common research topics for robot manipulators. The control of the modern robot manipulators are usually based on the measurements which are obtained through the motor angles. In order to improve the estimate of the end-effector position form these measurements, state estimators have been widely used. Kalman filter for linear systems and its variation for nonlinear systems such as Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), have been one of the most popular state estimation techniques for state estimation purposes (Auger et al., 2013; Simon, 2006; Shabbouei Hagh et al., 2016). Different methods have been developed to sense practical systems' movements/positions (Petković et al., 2013c; Petkovic et al., 2013b). On the other hand, enhancing the trajectory tracking performance is the other aspect for which considerable efforts have been made to develop new advanced control strategies. Finally adaptive and robust control strategies have been proposed that guarantees the globally asymptotical convergence of tracking errors (Chen and Lu, 2014; Yao et al., 2011).

Conventional Sliding Mode Control (SMC), due to its fast response, easy implementation and robustness to external disturbances, is one the most popular nonlinear control schemes which have been applied in many nonlinear systems (Basin and Rodriguez-Ramirez, 2014; Liang et al., 2012; Abdulhamitbilal and Jafarov, 2012). In some references, an adaptive version of the sliding mode control is presented to have a better performance (Huang et al., 2008; Chang et al., 2002; Guo and Woo, 2003). One of the main drawback of the SMC used in these papers is the asymptotic stable performance of the system controlled by SMC. To overcome this issue and have a finite time state convergence, a new controller named Terminal SMC (TSMC) has been proposed (Zak, 1988). In this method a one nonlinear term was added to the sliding surface to improve the convergence of the system. The TSMC has not only the benefits of the SMC, but also improves stability and performance of the system and speeds up the convergence time near an equilibrium point (Xu, 2013; Feng et al., 2002). However, the nonlinear term used in the TSMC may cause a singularity problem leading to a control magnitude to become unbounded. This problem has been studied and discussed in Feng et al. (2013) and has been solved by a new type of SMC controller named Nonsingular TSMC (NTSMC) . The proposed controller has the advantages of the SMC and TSMC and at the same time resolves the singularity phenomenon reported by using TSMC. The main drawback of these variations of SMCs is the phenomenon called chattering caused by the discontinuous part of the SMC while leading to high stress of mechanical/electrical elements. Methods have been proposed to overcome this problem (lyas, 2010). Methods of artificial intelligence, such as evolutionary algorithms, neural networks, and fuzzy sliding mode have a wide usage (Palm, 1992, 1994; Palm and Driankov, 1997). These methods are widely used for controlling and estimating different kinds of systems (Kankashvar et al., 2015; Mohammadi Asl et al., 2015; Nobarian et al., 2016). Knowledge based systems, such as TRIZ and fuzzy systems, are used in different applications (Petković et al., 2013b, 2012; Petković and Pavlović, 2013a). In Petkovic et al. (2013a), a knowledge based system

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has been developed to control a passively adaptive compliant gripper (Petković et al., 2013d). Being one of the strong methods of artificial intelligence, machine learning and neural networks have been applied for modeling and control of linear and nonlinear systems (Petković et al., 2016; Lian, 2014; Kazemlou and Mehraeen, 2014). Using this instrument has a good effect on the response of the system, and because of that it has a big usage. For instance, a chebyshev neural network has been combined with terminal sliding mode to control a space craft (Zou et al., 2011).

Considering the fact that knowing the system states are necessary to solve many control problems, observers such as Kalman Filters are used. One of the most popular variations of the KF-based state estimation method is Extended Kalman Kilter (EKF). This filter linearizes the system around the operating point at each time step which is done by calculating Jacobian matrices. This method requires the state dynamics to be differentiable. Hence, an Unscented Kalman Filter (UKF) has been introduced which uses the direct nonlinear model of the system and does not need the Jacobian calculation of the EKF (Julier and Uhlmann, 2004). All these variations are influenced by the accuracy of the knowledge of the noise statistics. The accuracy of the knowledge about the process and the measurement noise covariance matrices is important because any mismatch between the real noise distribution and the estimated one by any KF-based algorithm may result in a false data estimation. This legitimatize the study of adaptive estimation of the process and measurement noise covariances. To this end, there are classical methods (Shi et al., 2002; Agamennoni et al., 2012; Chang, 2014; Li et al., 2013), and also methods that use evolutionary algorithms such as genetic algorithm (Shi and Li, 2003), or particle swarm optimization (Laamari et al., 2015). As a strong evolutionary algorithm, charged system search (CSS) algorithm has been recently introduced (Kaveh and Talatahari, 2010), which has been applied to solve different engineering problems (Kaveh and Talatahari, 2012; Chu and Tsai, 2013). Despite of the high advantages of this method, it has some disadvantages. The highest disadvantage lays in its updating procedures. In its updating procedure, the value of the fitness is not considered in a proper way, which needs to be further developed and improved.

In this paper, a new neural network Non-singular Terminal Sliding Mode Control (NN-NTSMC) based on optimal Unscented Kalman Filter (OUKF) is investigated. It is assumed, that for the external disturbances an optimal Unscented Kalman Filter is applied to estimate the system's states. A new evolutionary algorithm tunes its covariance matrices because of this the proposed observer is called optimal. A new modified "charged system search" is introduced for this tuning. The proposed new modified algorithm has a fine tuning, because it adapts itself by the time. After system estimation, a neural network based Non-singular Terminal Sliding Mode Control are employed to control the estimated system. The proposed method is applied to estimate and control the states of a robotic manipulator.

The rest of this paper is arranged in four sections. Methods and materials, which are used for designing the proposed method, are reviewed in Sections 2 and 3. Section 4 presents the control of a robot manipulator and simulation results. Finally, the paper is concluded in Section 5.

## 2. The proposed intelligent observer

In this section, methods are reviewed, which are used for designing the proposed intelligent observer. First, a modified charged system search is introduced, which is developed in a way that adapts itself by the time. After that, Unscented Kalman Filter is reviewed, which is combined with the proposed modified evolutionary algorithm, and applied to estimate the states of the system.

### 2.1. Unscented kalman filter (UKF)

In order to approximate the nonlinearities of the system's dynamics, the EKF uses first-order linearization of the nonlinear system, during this linearization the higher order terms are being truncated. The main drawbacks of the EKF can be mentioned as, easy to be divergent, difficult to implement, slow convergence of parameter estimations (Haykin, 2004). To overcome the shortcomings of the EKF, UKF was developed by Julier and Uhlmann (2004). This filter is based on the sigma point implementation, known as unscented transform. This transformation is used to propagate means and covariance of the state variable. These carefully chosen weighted sigma points can capture the true *a posterior* mean and covariance. Hence, UKF yields in superior performance compared to EKF. Consider the following nonlinear system:

$$\begin{aligned} x_k &= f(x_{k-1}, u_{k-1}) + w_{k-1} \\ y_k &= g(x_k) + v_k \end{aligned} \tag{1}$$

where $x \in R^n$ and $y \in R^r$ and $u \in R^m$ represent the state vector, measured outputs and controlled inputs, respectively, and $k$ is the sampling interval. The $f$ and $h$ function describe the nonlinear dynamic and measurement model of the system. $w_k$ and $v_k$ are Gaussian white noise distributions with zero mean and $R$ and $Q$ covariance matrices, respectively. The algorithm of the Unscented Kalman Filter (UKF) can be summarized as follows:

The algorithm begins with some initial guesses for the error covariance matrix $(P)$ and state estimation $x$ as

$$\begin{aligned} \hat{x}_0 &= E[x_0] \\ P_0 &= E[(x_0-\hat{x}_0)(x_0-\hat{x}_0)^T] \end{aligned} \tag{2}$$

Then the sigma points should be calculated. To this end, *priori* state $(\hat{x}_{k-1})$ and error covariance $(P_{k-1})$ should be used, as:

$$\begin{aligned} \mathcal{X}^{(i)}_{k-1|k-1} = [&\hat{x}_{k-1|k-1}, \hat{x}_{k-1|k-1} + \sqrt{L+\lambda}\sqrt{P_{k-1|k-1}}, \hat{x}_{k-1|k-1} \\ &- \sqrt{L+\lambda}\sqrt{P_{k-1|k-1}}] \end{aligned} \tag{3}$$

Here, $L$ is the number of states, $\lambda$ is a scaling parameter defined as $\lambda = \alpha^2(L+\kappa) - L$. The $\kappa \ge 0$ should be chosen properly in order to guarantee the covariance matrix to be semi-positive definite. Usually $\kappa = 0$ is an appropriate choice. The parameter $\alpha$ controls the distribution size of these sigma points and it should be tuned as $0 < \alpha \le 1$. This parameter should be a small number (Van Der Merwe, 2004). The $\sqrt{P_{k-1|k-1}}$ term is the Cholesky factor of $P_{k-1|k-1}$. Now, each of these sigma points should propagate through nonlinear $f$ function

$$\gamma^{(i)}_{k|k-1} = f(\mathcal{X}^{(i)}_{k-1|k-1}, u_{k-1}), \quad i = 0, 1, \ldots, 2L \tag{4}$$

now that these points propagated, the *posterior* mean and covariance matrix can be calculated:

$$\begin{aligned} \hat{x}_{k|k-1} &= \sum_{i=0}^{2L} w_i^{(m)}\gamma^{(i)}_{k|k-1} \\ P_{k|k-1} &= \sum_{i=0}^{2L} \{w_i^{(c)}(\gamma^{(i)}_{k|k-1}-\hat{x}_{k|k-1})(\gamma^{(i)}_{k|k-1}-\hat{x}_{k|k-1})^T\} + Q_{k-1} \end{aligned} \tag{5}$$

where $w_i^{(m)}$ and $w_i^{(c)}$ are sets of predefined weights by

$$\begin{aligned} w_0^{(m)} &= \frac{\lambda}{L+\lambda} \\ w_0^{(c)} &= \frac{\lambda}{L+\lambda} + (1-\alpha^2+\beta) \\ w_i^{(m)} &= w_i^{(c)} = \frac{1}{2(L+\kappa)} \quad ; i = 1, \ldots, 2L \end{aligned} \tag{6}$$

where $\beta$ is non-negative tuning parameter that is set as $\beta = 2$ for a Gaussian prior distribution (Van Der Merwe, 2004). Next, the measurement update step should be calculated. First, the sigma point should be updated

$$\mathcal{X}^{(i)}_{k|k-1} = [\hat{x}_{k|k-1}, \hat{x}_{k|k-1} + \sqrt{L+\lambda}\sqrt{P_{k|k-1}}, \hat{x}_{k|k-1} - \sqrt{L+\lambda}\sqrt{P_{k|k-1}}] \tag{7}$$

then, each column of the $\mathcal{X}^{(i)}_{k|k-1}$ will propagate through nonlinear