# 論文 / 著書情報
# Article / Book Information

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# 論 文 要 旨

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要旨（英文 800 語程度）
Thesis Summary (approx.800 English Words )


Outliers are a kind of non-Gaussian measurement noise generated by heavier tailed distributions than a normal distribution. Hence, abnormal values, which are distant so much from mean values of distributions, In other words, the outliers are contained in measurements infrequently and their values can usually be considered as zero, so it can be said that the outliers tend to be sparse. They are happened in many applications, and they provide negative effects on various fields. In control engineering, these outliers deteriorate state estimates and control performances. For example, target tracking systems using radar measurement, visual feedback systems, wireless sensor network systems, networked control systems, and so on. Therefore, control systems require robust estimators and controllers under outliers. We propose a practical robust estimation method and control strategy under outliers based on robust Kalman filter (RKF) via $l_1$ regression. In addition, we analyze performances of the proposed methods, and the effectiveness is demonstrated by some numerical simulations.

RKF via $l_1$ regression is one of the most attractive reduction methods of effects of outliers due to an easy structure and implementation. Additionally, Since the RKF truncates outliers by some thresholds, it has less delay than the other RKF. However, regularization parameters of the RKF need to be tuned by some heuristic design methods. First of all, we propose a new design method of the RKF. Both primal and dual problems can derive a condition of the proposed parameters, and it is shown that statistics of Gaussian noise determine the parameters of the RKF. This means that the proposed design method provides the parameters with physical meanings, and we can design the parameters systematically. It is also shown that a covariance matrix of an innovation of the RKF is bounded by that of normal Kalman filter (KF) without outliers. The covariance matrix of the innovation of the RKF comes close to an ideal one under outliers. The RKF with the proposed design method is applied to a target tracking system under clutters and two-wheeled vehicle control with outliers.

The RKF can be formulated as a $l_1$ optimization problem. In general, the optimization problem cannot be solved analytically, and some numerical iterative methods are needed. A convergence rate and accuracy of the solutions of the RKF depend on conditions of the iterations. Secondly, we propose a closed form solution of the RKF by an approximation of its optimal solution, and it gives a fast algorithm. The approximated solution can be calculated by upper and lower bounds of the optimal solution. In addition, an estimation error of the approximated solution is analyzed. It is shown that the proposed algorithm has almost same performances as KF without outliers under some conditions.

Moreover, in order to construct a robust controller under outliers, we apply an idea of the RKF to self-tuning controller (STC), and we propose a robust STC (RSTC) under outliers. A parameter update law of the conventional STC can be written as a recursive least square (RLS) estimation, and RLS estimation can be given by a solution of a minimization problem of estimated errors. Therefore, the proposed method estimates parameters and outliers explicitly by addition of a $l_1$ regression term to the minimization problem, and the estimated outliers are removed from measurement outputs in a controller. The proposed method is solved in a closed form because of a $l_1$ optimization problem with a single variable, so the algorithm is very efficient. In order to guarantee a stability of the controller, it is required not only to reduce effects of the outliers, but also to analyze performances of the reduction method. We analyze

control performances of the proposed method under outliers, and it is shown that steady state errors in the proposed RSTC are nearly equal to ones in the conventional STC without outliers.

For nonlinear systems, extended KF (EKF) is often used to extend the aforementioned methods. However, EKF needs to compute Jacobians of the nonlinear systems and yields unstable solutions numerically. Gaussian sum filter and Particle filter are other famous KF for nonlinear systems and non-Gaussian measurement noise including outliers. They can approximate arbitrary distributions and can provide global optimal estimates. However, it takes so long time to compute the algorithms, and it is unsuitable for real time applications. Finally, we extend the RKF to nonlinear systems by using unscented KF (UKF), and we propose a robust UKF (RUKF). We also propose a new design method of its regularization parameters. Similarly to linear systems, it is shown that statistics of Gaussian measurement noise determine the parameters of RUKF, and we can design the parameters systematically. And also, the proposed design method provides the parameters with physical meanings. Moreover, the regularization parameters make performances of RUKF come close to ones of UKF without outliers. Since RUKF is based on UKF and $l_1$ optimization problem, it can be computed more efficiently than Gaussian sum filter and particle filter.