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Original article

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GENERALIZED TECHNIQUE FOR OPTIMIZING THE PARAMETERS OF TRACKING ESTIMATORS OF COORDINATES AND MOTION PARAMETERS IN AIR AND GROUND SITUATION MONITORING SYSTEMS

Abstract. The paper presents the results of research and development of a methodology for optimizing parameters of tracking estimators for object coordinates and motion parameters. The methodology is based on a comprehensive approach to training dataset formation considering various types of object motion and application of specialized optimization algorithms. The developed algorithms implement a complete optimization cycle, including training dataset formation, data preprocessing, parameter optimization, and verification of obtained results. The results of practical application of the methodology for optimizing parameters of non-adaptive Kalman filter and Interacting Multiple Model (IMM) filter under various observation conditions and object motion patterns are demonstrated. Based on simulation modeling, it is shown that the application of the developed methodology significantly improves the accuracy of estimating coordinates and motion parameters compared to traditional approaches to parameter selection. Special attention is paid to studying the stability of obtained solutions to changes in observation conditions and object motion patterns. The obtained results are advisable to use in development and modernization of radar data tracking systems, air traffic control systems, air and ground situation monitoring complexes, as well as in other applications requiring high-precision estimation of object motion parameters under a priori uncertainty.

Keywords: tracking estimator, parameter optimization, Kalman filter, IMM-filter, maneuvering object, training dataset, a priori uncertainty, estimation accuracy

Conflict of interest: the author declares that there is no conflict of interest.

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ОБОБЩЕННАЯ МЕТОДИКА ОПТИМИЗАЦИИ ПАРАМЕТРОВ ТРАЕКТОРНЫХ ИЗМЕРИТЕЛЕЙ КООРДИНАТ И ПАРАМЕТРОВ ДВИЖЕНИЯ В СИСТЕМАХ МОНИТОРИНГА ВОЗДУШНОЙ И НАЗЕМНОЙ ОБСТАНОВКИ

Аннотация. Представлены результаты разработки и исследования обобщенной методики оптимизации параметров траекторных измерителей координат и параметров движения в системах мониторинга воздушной и наземной обстановки. Методика основана на комплексном подходе к формированию обучающей выборки с учетом различных моделей движения объектов и применении специализированных алгоритмов оптимизации. Разработанные алгоритмы реализуют полный цикл оптимизации, включая формирование обучающей выборки, предварительную обработку входных данных, совершенствование параметров и верификацию полученных результатов. Продемонстрированы результаты практического применения методики для настройки параметров неадаптивного фильтра Калмана и многоканального адаптивного фильтра (Interacting Multiple Model, IMM) при различных условиях наблюдения и характере движения объектов. На основе имитационного моделирования показано, что применение разработанной методики позволяет существенно повысить точность оценивания координат и параметров движения объектов по сравнению с традиционными подходами к выбору параметров. Особое внимание уделено исследованию устойчивости полученных решений к изменению условий наблюдения и характера движения объектов. Полученные результаты целесообразно использовать при разработке и модернизации систем траекторной обработки радиолокационной информации, в системах управления воздушным движением, при создании комплексов мониторинга наземной и воздушной обстановки, а также в других приложениях, требующих точного оценивания координат и параметров движения объектов в условиях априорной неопределенности.

Ключевые слова: траекторный измеритель, оптимизация параметров, фильтр Калмана, IMM-фильтр, маневрирующий объект, обучающая выборка, априорная неопределенность, точность оценивания

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Introduction. The optimization of tracking estimators for coordinates and motion parameters is one of the key challenges in modern air and ground situation monitoring systems [1–4]. This task becomes particularly relevant when tracking maneuvering objects, where high estimation accuracy is required under conditions of a priori uncertainty in object motion patterns [6, 7]. Recent years have seen significant progress in the development and improvement of trajectory filtering algorithms [2, 5, 7, 8]. Modern approaches allow for substantial improvement in motion parameter estimation accuracy through the use of adaptive and multiple-model methods. However, the selection and tuning of estimator parameters that determine their performance under various operating conditions remains a crucial issue [3, 7, 8]. Despite significant achievements in this field, existing approaches to tracking estimator optimization have several limitations: complexity in accounting for a priori uncertainty of various models of object motion; insufficient development of comprehensive estimator parameter optimization; and difficulties in practical implementation of the proposed optimization algorithms. This paper presents a method for optimizing tracking estimators aimed at overcoming these limitations. The method is based on a systematic approach to training dataset formation and the application of specialized optimization algorithms that consider the specifics of both non-adaptive and adaptive estimators. Special attention is paid to the practical feasibility of the proposed solutions.

The *aim of this work* is to improve the accuracy of estimating coordinates and motion parameters of objects by optimizing tracking estimator parameters while accounting for a priori uncertainty in the motion patterns of observed objects.

Generalized Technique for Optimizing Tracking Estimators. The developed technique for optimizing tracking estimators represents a seven-stage process that provides a systematic approach to solving the parameter tuning problem for estimators of coordinates and motion parameters of various object classes.

The first stage involves initial data formation, including specification of observed object classes and their motion models. In air and ground situation monitoring systems, various object classes can be observed [1, 7]: aerial (including aerodynamic aircraft, helicopters, unmanned aerial vehicles), ground (cars, trucks, people) and false objects. Each class is characterized by its specific motion models that are incorporated into the multi-channel IMM filter structure. This takes into account limitations on the estimator structure, selection of possible parameter ranges for tracking filters for each object class, and determination of estimation quality criteria, such as root mean square (RMS) errors of coordinates and motion parameters.

The second stage includes preparation of the training dataset by generating typical trajectories for each object class. During dataset formation, various motion scenarios are simulated [1–4, 7]: straight-line uniform motion, movements with maneuvers of varying intensity, motion with velocity changes and other. An important aspect is the integration of real experimental data and simulation of primary sensor measurement noise considering their actual characteristics.

The third stage involves optimizer setup, which includes formalization of the objective function as RMS estimation error minimization, definition of constraints on optimized parameters, selection of initial search points, and tuning of optimization algorithm parameters [9]. Special attention is paid to defining optimization process stopping criteria.

The fourth stage is dedicated to direct optimization of the estimator structure. During this stage, the optimal number of channels for each object class is determined, and filter types are selected for the channels [1, 4]: linear Kalman filters of various orders, quasi-linear filters, nonlinear filters, and specialized filters such as the Singer filter. Individual filter parameters are tuned, and in the case of IMM (Interacting Multiple Model) structure, the transition probability matrix between channels is optimized, and their interaction algorithms are configured.

The fifth stage provides validation of obtained results by testing solutions on a test trajectory dataset. Solution stability is evaluated under various conditions, including different initial conditions, maneuver types, and measurement noise levels. Computational cost analysis and comparative analysis with baseline estimator variants are performed.

The sixth stage involves forming recommendations, including compilation of optimal parameter tables for various object classes, determining solution applicability conditions, developing practical implementation recommendations, and evaluating expected accuracy improvements for various application conditions.

The final seventh stage includes adaptive algorithm implementation, which involves software implementation of the optimized structure, configuration of inter-model interaction mechanisms, implementation of parameter adaptation algorithms, and real-time testing followed by result documentation.

Practical Implementation of the Technique. Measuring object angles is one of the key tasks in air and ground situation monitoring systems [1, 2, 4]. As a practical example, the task of tracking a maneuvering aerial object using only angular measurement information from a stationary direction finder was considered. In this single-sensor configuration, it is impossible to directly reconstruct the full spatial coordinates of the object, making the problem particularly challenging. The initial conditions are characterized by the following parameters: the RMS error of bearing measurement is 1 degree, with a data update interval of 10 s. During model experiments, trajectories were considered where the aerial object moved at a constant velocity of 220 m/s at an altitude of 1 km. Between the 32 and 41 scans of the direction finder, the object performed a steady turn in the horizontal plane at angles of 180, 270, and 360 degrees with normal acceleration n_y = 1.1, 1.5, and 2.0, depending on the specific trajectory. As shown in Figure 1, all trajectories are characterized by significantly nonlinear bearing change patterns. These strong nonlinearities in bearing measurements require approximation using high-order polynomials and create additional challenges for filtering algorithms [2, 4].

At the first stage of the study, a direct parameter search was conducted for a non-adaptive Kalman filter [1, 7, 8]. This approach, while conceptually straightforward, proved to be computationally intensive due to the need for exhaustive search across the parameter space. Figure 2 shows the dependence

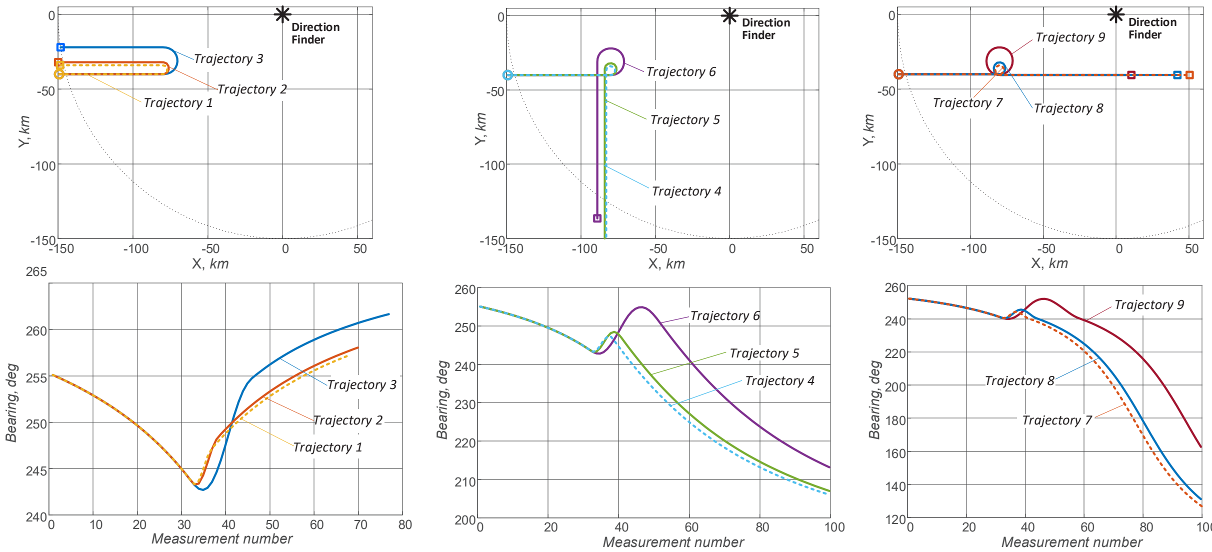

Figure 1. Trajectories and bearing change patterns for model experiments: trajectories *1–3* – with 90°, trajectories *4–6* – with 180°, and trajectories *7–9* – with 270° turns, each set at normal accelerations n_y = 1.1, 1.5, and 2.0

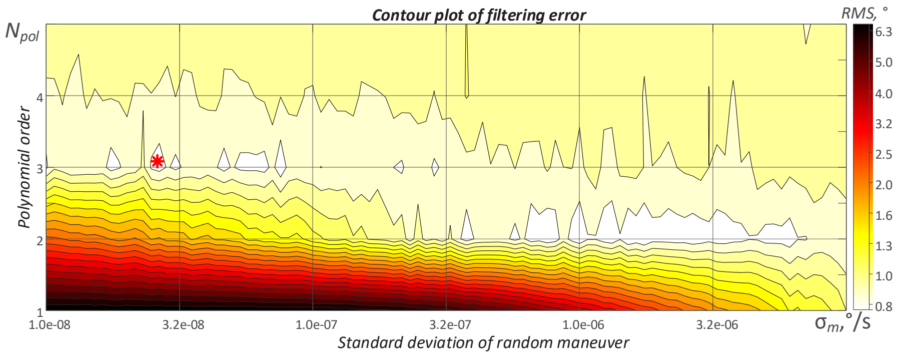

Figure 2. Dependence of total bearing filtering error on polynomial order and RMS random maneuver value

of the total bearing filtering error (averaged over all selected object trajectories) on the polynomial order and RMS random maneuver value. Analysis of the results revealed a complex multi-modal nature of the error surface, with several local minima, making the optimization process particularly challenging. Nevertheless, it was found that there exists an optimal combination of these parameters that provides minimal filtering error.

Further optimization of the Kalman filter was conducted using the developed technique. For this purpose, an algorithm based on *the Pattern Search method* was implemented [9]. The algorithm searches for optimal values of two key Kalman filter parameters: polynomial order N_{pol} and random maneuver standard deviation σ_m. The distinctive feature of the implemented algorithm is its adaptive search step and extended set of parameter space exploration directions, including both primary and diagonal directions. The search is performed within the space of permissible values, where the polynomial order varies from 1 to 5, and σm ranges from 10^{-8} to 10^{-5}. The optimization process starts from an arbitrary point (N_{pol} = 1, $\sigma_{\text{m}} = 10^{-8}$) and sequentially improves the solution by minimizing the root mean square error of bearing filtering. To enhance computational efficiency, result caching is implemented, which helps avoiding repeated calculations for previously investigated parameter combinations. As shown in the graphs in Figure 3, the optimization process demonstrates stable convergence. After approximately 30 iterations, optimal parameter values are achieved: N_{pol} = 2 and $\sigma_{\text{m}} \approx 3.9 \cdot 10^{-8}$. With these parameters, the RMSE of bearing filtering is minimal at about 0.7 degrees, which is 30 % lower compared to the non-optimized filter.

The effectiveness of the optimized filter is confirmed by the results of filtering real trajectories (Figure 4), where significant improvement in bearing estimation quality is observed, especially in the object

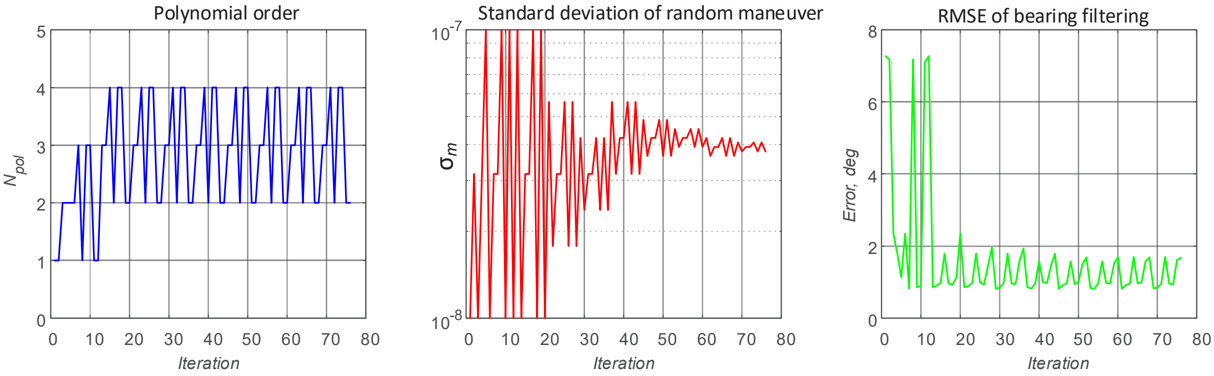

Figure 3. Illustration of the non-adaptive filter optimization procedure

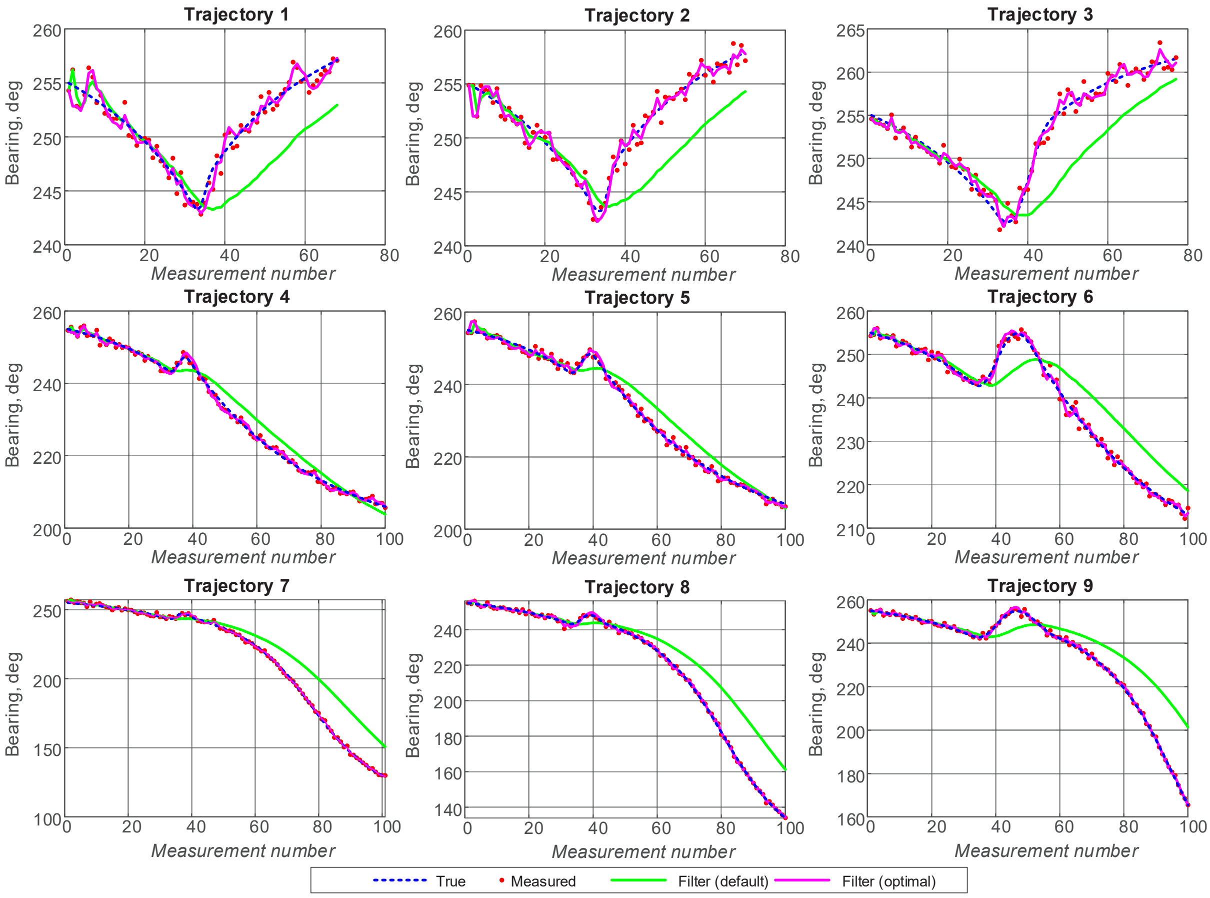

Figure 4. Comparison of non-adaptive filtering results for non-optimized and optimized filters

maneuvering region (from scan 32 to 41), with the optimized filter (magenta line) demonstrating superior tracking performance and better measurement noise suppression compared to the default filter (green line) throughout the entire trajectory.

IMM filter is one of the most effective adaptive filtering algorithms due to its ability to dynamically combine results from multiple motion models [1, 3, 4]. This enables high estimation accuracy both during uniform motion and various object maneuvers. However, tuning IMM filter parameters represents a complex optimization problem due to the large number of interrelated parameters and their nonlinear influence on filtering quality. The IMM filter includes three channels [1, 3, 4, 6, 7]: first- (constant velocity – CV) and second-order (constant acceleration – CA) Kalman filters, and a first-order Singer filter. The following parameters were optimized using genetic algorithm: σ_{CV} – RMS random maneuver for CV filter (from 10^{-6} to 10^{-2}); σ_{CA} – RMS random maneuver for CA filter (from 10^{-6}

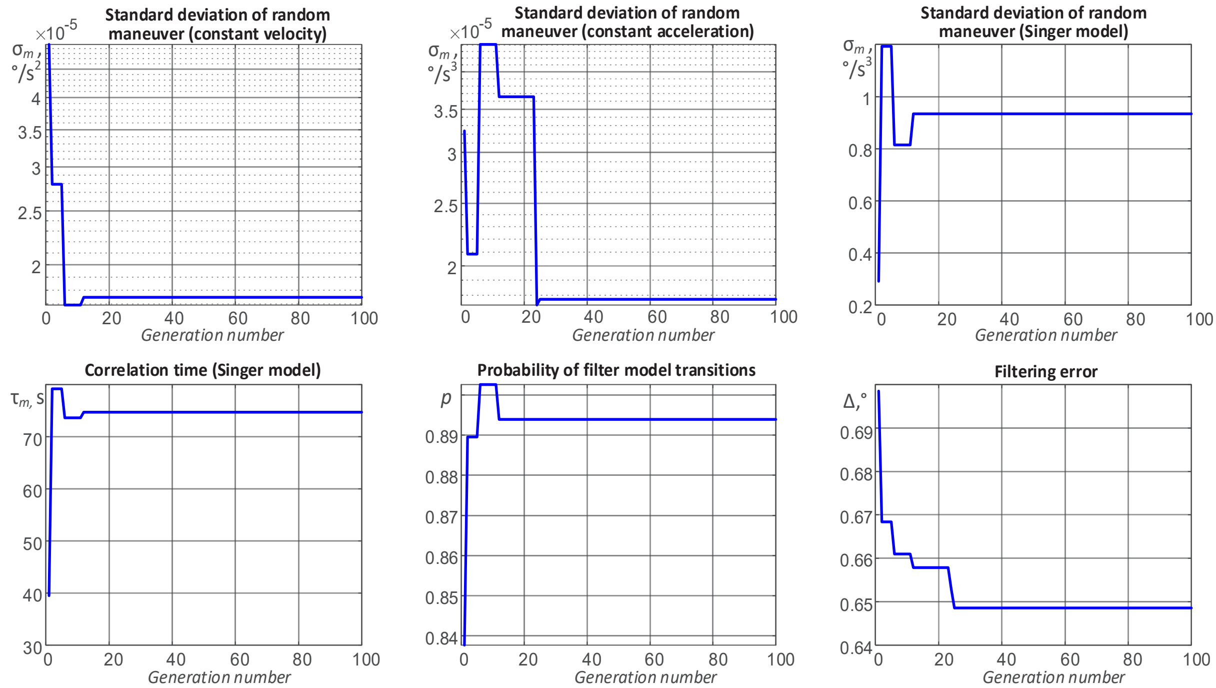

Figure 5. Illustration of the adaptive IMM filter optimization procedure

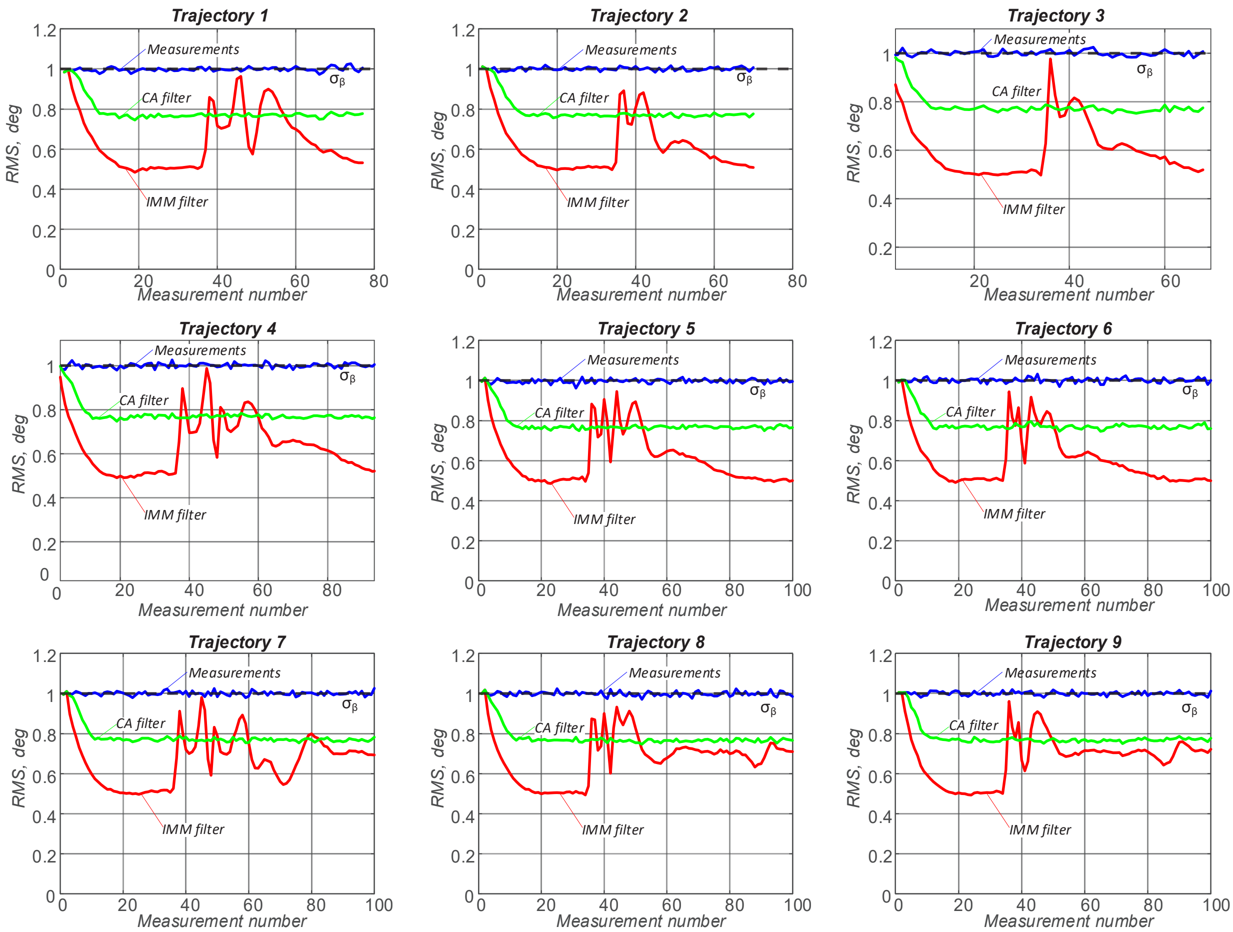

Figure 6. Comparison of optimized filtering algorithm results

to 10^{-2}); σ_{Singer} – RMS random maneuver in Singer model (from 0.1 to 2.0); τ_m – maneuver time constant (from 30 to 90 s); p – probability of IMM filter model transitions (from 0.8 to 0.95). The algorithm features adaptive mutation, logarithmic scaling for σ_{CV} and σ_{CA}, elitist strategy, and tournament selection. As shown in Figure 5, the optimization converges after approximately 50 generations, yielding optimal values: $\sigma_{CV} \approx 2.8 \cdot 10^{-4}$; $\sigma_{CA} \approx 1.5 \cdot 10^{-3}$; $\sigma_{\text{Singer}} \approx 1.2$; $\tau_m \approx 45$ s; $p \approx 0.92$.

Comparative analysis results (Figure 6) show that the optimized IMM filter provides: 40 % reduction in root mean square error of bearing estimation compared to the non-adaptive Kalman filter; faster adaptation to object maneuvers; stable operation under various types of maneuvers; shorter transient response time during changes in object motion patterns. The Figure 6 presents nine different trajectory scenarios 1–9, each showing the comparison between measurement data (blue line), IMM filter performance (red line), and CA filter performance (green line, using optimal parameters previously obtained in Figures 3 and 4 for the non-adaptive case). All RMS error values were calculated by averaging results over 5,000 Monte Carlo runs to ensure statistical significance of the comparison. The IMM filter consistently demonstrates lower RMS errors during steady-state periods compared to both raw measurements and the CA filter. During maneuver periods (visible as spikes in the plots around 400 s), the IMM filter shows temporary increase in RMS error but recovers more quickly than the CA filter. The CA filter maintains a relatively stable error level but fails to achieve the same level of accuracy as the IMM filter during both steady-state and maneuvering periods. Trajectories *7–9*, which represent the most complex maneuvers (270° turns), show the IMM filter's superior ability to handle challenging scenarios while maintaining stable performance. The measurement noise level (approximately 1 degree RMS) is effectively filtered by both algorithms, with the IMM filter achieving better overall performance, especially during the post-maneuver settling period. The time scale extends to 800–1,000 s, providing sufficient duration to observe both transient and steady-state behavior of the filtering algorithms across various maneuver scenarios.

Conclusion. This paper presents a practical implementation for optimizing tracking estimators of coordinates and motion parameters in air and ground situation monitoring systems. Key research outcomes include development of a multi-stage optimization technique for both non-adaptive and adaptive estimators, implementation of a pattern search optimization algorithm for non-adaptive Kalman filter (achieving $N_{\text{pol}} = 2$ and $\sigma_m \approx 3.9 \cdot 10^{-8}$), and development of a specialized genetic algorithm for IMM filter optimization (achieving $\sigma_{CV} \approx 2.8 \cdot 10^{-4}$, $\sigma_{CA} \approx 1.5 \cdot 10^{-3}$, $\sigma_{\text{Singer}} \approx 1.2$, $\tau_m \approx 45$ s, $p \approx 0.92$).

Model experiments with various aircraft trajectories (180°, 270°, and 360° turns with load factors n_y = 1.1, 1.5, and 2.0) confirmed the effectiveness of the developed methodology, demonstrating improved motion parameter estimation accuracy, better adaptation to object maneuvers, stable operation under various motion models, and reduced transient response times. Future research directions may include extending the methodology to other types of measurement information and observed object classes.

References

1. Blackman S., Popoli R. *Design and Analysis of Modern Tracking Systems*. Boston, Artech House, 1999. 1230 p.

2. Radhika M., Mallick M., Tian X. IMM Filtering Algorithms for a Highly Maneuvering Fighter Aircraft: An Overview. *Algorithms*, 2024, vol. 17, no. 9, pp. 399–415. http://doi.org/10.3390/a17090399

3. Bar-Shalom Y., Rong Li X., Kirubarajan T. *Estimation with Applications to Tracking and Navigation*. New York, Wiley-Interscience Publ., 2001. 558 p. https://doi.org/10.1002/0471221279

4. Ristic B., Arulampalam S., Gordon N. *Beyond the Kalman Filter. Particle Filters for Tracking Applications*. Boston, London, Artech House, 2004. 299 p.

5. Han B., Huang H., Lei L., Huang C., Zhang Z. An Improved IMM Algorithm Based on STSRCKF for Maneuvering Target Tracking. *IEEE Access*, 2019, vol. 7, pp. 57795–57804. https://doi.org/10.1109/ACCESS.2019.2912983

6. Singer R. A. Estimating optimal tracking filter performance for manned maneuvering targets. *IEEE Transactions on Aerospace and Electronic Systems*, 1970, vol. 6, no. 4, pp. 473–483. https://doi.org/10.1109/TAES.1970.310128

7. Li X. R., Jilkov V. P. Survey of Maneuvering Target Tracking. Part I: Dynamic Models. *IEEE Transactions on Aerospace and Electronic Systems*, 2003, vol. 39, no. 4, pp. 1333–1364. https://doi.org/10.1109/TAES.2003.1261132

8. Grewal M. S., Andrews A. P. *Kalman Filtering: Theory and Practice with MATLAB*. Wiley, 2014. 640 p. https://doi.org/10.1002/9780470377819

9. Yang X. S. *Nature-Inspired Optimization Algorithms: Theory, Advances and Applications*. 2^{nd} ed. London, Academic Press, 2021. 446 p. https://doi.org/10.1016/C2019-0-02835-0