Secure Systems Design and Technology Development. Veliko Tarnovo, Bulgaria
Proceedings of the International Scientific Conference, 2026. Volume II, 397-403

Bayesian Method for Recursive Combination of Measurement and Prior Information for Accuracy Improvement in Video-Based Measurements

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***Abstract*— This paper presents a Bayesian method for the recursive combination of prior and measurement information aimed at improving the accuracy of video-based measurements. The proposed approach is based on a probabilistic formulation in which measurements are affected by stochastic noise with time-varying characteristics. The main contribution is the development of an adaptive mechanism for estimating the measurement noise variance, based on normalized innovation and a variable smoothing coefficient. This enables dynamic adjustment of the influence of measurements according to their current reliability, without the need for an explicit dynamic model. The effectiveness of the method is evaluated through simulations at different noise levels, with results demonstrating robust and accurate estimation, effective suppression of noise-induced deviations, and consistent uncertainty quantification. The method is applicable to machine vision and video-based object tracking tasks under varying measurement conditions.**

Keywords*— *Video-based measurements; machine vision; object tracking; Bayesian estimation; recursive methods; measurement noise variance.

I. INTRODUCTION

Modern machine vision and video surveillance systems are widely used in various fields, including manufacturing automation, robotics, intelligent transportation systems, and security systems [1], [2]. In these applications, it is often necessary to determine the coordinates of observed objects with high accuracy based on information from sequential video frames [2], [3].

One of the main challenges in video-based measurements is the presence of measurement noise caused by limited image resolution, variable lighting conditions, image artifacts, and inaccuracies in visual data processing [4]-[7]. These factors lead to significant deviations between the measured and true coordinates and limit the accuracy of estimation [8], [9].

Probabilistic estimation methods based on the Bayesian framework, including the Kalman filter and its extensions, are widely used worldwide to address these issues [10]-[14]. These methods enable the combination of prior information and current measurements to reduce the influence of noise [15], [16]. However, in most cases, they rely on predefined or weakly adaptive parameters that

Online ISSN 3044-7771
https://doi.org/10.68302/std2026.vol2.203

determine the relative confidence in the measurements [17], [18].

A significant limitation of classical approaches is that the measurement noise variance is often assumed to be constant or determined a priori, without accounting for its temporal variation [19]-[22]. Under real-world conditions, however, measurement quality may vary dynamically, leading to a degradation in the performance of methods with fixed parameters [23]-[34].

This paper proposes a Bayesian method for the recursive combination of prior and measurement information, in which an adaptive mechanism for estimating the measurement noise variance is introduced. The proposed approach enables automatic adjustment of the influence of measurements according to their current reliability, without requiring an explicit dynamic model of the object's motion.

The primary contribution of this study is the development of an adaptive scheme for estimating the measurement noise variance, based on normalized innovation and a variable smoothing coefficient. This ensures improved robustness of the algorithm under varying measurement conditions and enhanced estimation accuracy.

II. Formulation of the Proposed Approach

The proposed approach is based on a recursive Bayesian scheme for state estimation in the presence of uncertainty and time-varying measurement quality. The main objective is to combine prior information and current measurements in a probabilistically consistent manner, while accounting for the dynamic variation in measurement reliability.

The algorithm is formulated in discrete time, where the index k denotes the current processing step or the corresponding video frame. The measurement process is described by an additive stochastic model that relates the object state to the measured value at step k.

$$z_k = x_k + v_k, \tag{1}$$

where x_k is the object state at step k, z_k is the measured value, and v_k is a random variable representing the measurement noise.

In the present study, x_k is considered as a scalar quantity derived from the image, for example, a coordinate in pixels along a selected axis. This assumption allows for a clear representation of the main relationships, while the obtained results can be readily extended to the multidimensional case.

In the model, the quantity v_k is assumed to have zero mean and variance $\sigma_z^2(k)$. Unlike the classical formulation, this variance is not considered constant, but rather as a time-varying quantity.

A. Recursive Bayesian Estimation

Prior to incorporating the current measurement, the available information about the object state is represented by the prior estimate $\hat{x}_k^-$ and its corresponding variance σ_k^{2-}. Within the considered algorithm, the prior estimate at step k is formed based on the result of the previous iteration.

Under Gaussian assumptions, the updated estimate is given by:

$$\hat{x}_k = \hat{x}_k^- + K_k e_k, \tag{2}$$

where the innovation is defined as:

$$e_k = z_k - \hat{x}_k^-, \tag{3}$$

and the gain K_k is given by:

$$K_k = \frac{\sigma_k^{2-}}{\sigma_k^{2-} + \sigma_z^2(k)}. \tag{4}$$

The corresponding posterior variance is given by:

$$\sigma_k^2 = (1 - K_k)\sigma_k^{2-}. \tag{5}$$

From these relationships, it follows that the contribution of the measurement is automatically determined by its reliability. For low measurement noise variance, the gain K_k increases and the estimate approaches the measured value, whereas for higher uncertainty, the algorithm assigns greater weight to the prior information.

B. Adaptive Estimation of the Measurement Noise Variance

A key element of the proposed method is the adaptive estimation of the measurement noise variance $\sigma_z^2(k)$, which enables the algorithm to account for variations in measurement conditions.

The initial value of the variance is determined based on the spatial discretization of the image. Assuming a uniform distribution of the error within a single pixel, it can be expressed as:

$$\sigma_z^2(0) = \frac{\Delta^2}{12}, \tag{6}$$

where Δ is the equivalent pixel size along the corresponding coordinate.

To account for variations in measurement conditions, the variance is updated recursively. For this purpose, the normalized innovation is defined as:

$$r_k = \frac{e_k^2}{\sigma_z^2(k-1) + \varepsilon}, \tag{7}$$

where $\varepsilon > 0$ is a small constant ensuring numerical stability.

Based on this quantity, an adaptive coefficient is determined:

$$\lambda_k = \lambda_{\min} + \frac{\lambda_{\max} - \lambda_{\min}}{1 + \alpha r_k}, \tag{8}$$

where $0 < \lambda_{\min} < \lambda_{\max} < 1$, and $\alpha > 0$ determines the sensitivity of the adaptation.

The parameter α controls the extent to which the normalized innovation influences the value of λ_k. For larger values of α, even small variations in r_k lead to a significant decrease in λ_k, thereby accelerating the adaptation of the algorithm. Conversely, for smaller values of α, the variation of λ_k is smoother, resulting in more inertial behavior and higher robustness to noise.

- formation of the innovation,
- adaptive estimation of the measurement noise variance,
- updating of the estimate and its variance.

At each iteration k, the current measurement z_k is compared with the available prior estimate, resulting in the innovation e_k. This quantity is used both in the adaptive procedure for estimating $\sigma_z^2(k)$ and in the Bayesian state update.

The updated measurement noise variance $\sigma_z^2(k)$ serves a dual function: it is involved in the computation of the gain K_k at the current step and, at the same time, is used as an

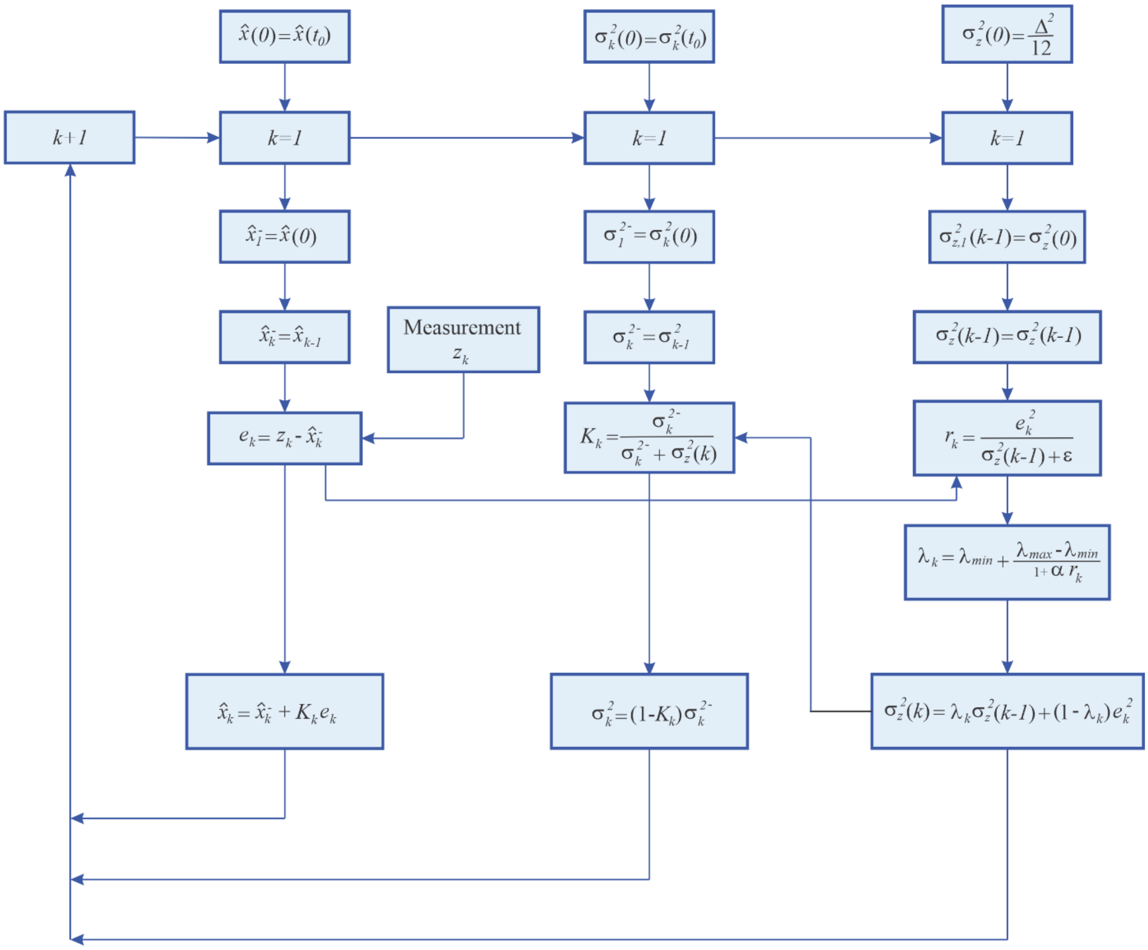


Fig. 1. Block diagram of the recursive algorithm and its parallel computational structure.

The measurement noise variance is updated as follows:

$$\sigma_z^2(k) = \lambda_k \sigma_z^2(k-1) + (1-\lambda_k)e_k^2. \tag{9}$$

In this way, a two-stage adaptation mechanism is achieved: first, the variance is updated based on the current innovation, and second, the update rate is dynamically adjusted.

C. Algorithmic Structure

The proposed method is implemented as a recursive procedure consisting of three parallel computational branches that provide:

input quantity for the next iteration. Similarly, the obtained values of the estimate $\hat{x}_k$ and its variance σ_k^2 are used in the subsequent step, ensuring the recursive nature of the algorithm.

A graphical representation of the algorithm, based on the three parallel computational branches and their interconnections described above, is shown in Fig. 1.

III. Simulation Results and Analysis

A. Simulation Conditions

The simulation study is focused on estimating the coordinate of an observed object in the presence of measurement noise. A one-dimensional quantity corresponding to the object position, derived from a video image, is considered.

The measurement process is described by the additive stochastic model (1).

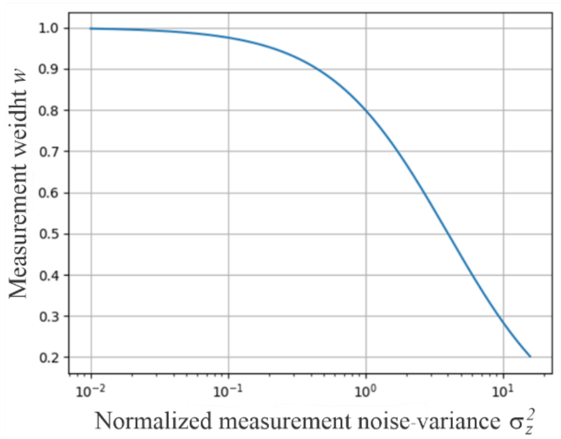
In the simulation, the noise v_k is assumed to have zero mean and variance $\sigma_z^2(k)$, which may vary over time in order to model different measurement conditions.

The initial value of the measurement noise variance is determined according to relation (6).

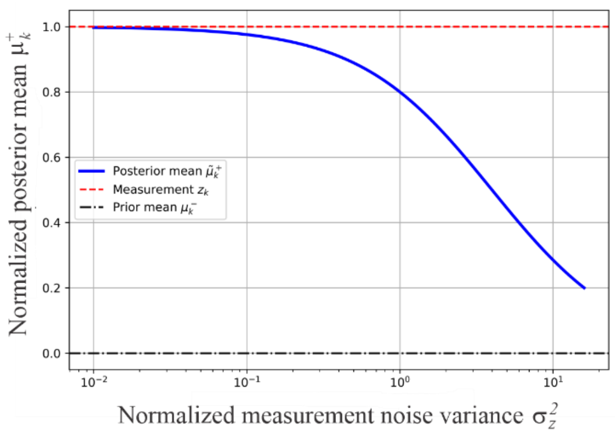
The prior and posterior state estimates, interpreted as the mean values of the corresponding probability distributions, are denoted by μ_k^- and μ_k^+, respectively, with the posterior estimate given by:

$$\mu_k^+ = \frac{\sigma_{z,k}^2 \mu_k^- + \sigma_k^{2-} z_k}{\sigma_k^{2-} + \sigma_{z,k}^2}. \tag{10}$$

The prior estimate μ_k^- is obtained from the posterior estimate at the previous iteration, reflecting the absence of an explicit dynamic model in the considered approach.



a)



b)

Fig. 2. Dependence of the weighting coefficient $w$and the normalized posterior estimate μ_k^+ on the measurement noise variance σ_z^2: (a) weighting coefficient w; (b) normalized posterior estimate μ_k^+.

For the purposes of the analysis, a weighting coefficient is also introduced:

$$w = \frac{\sigma_k^{2-}}{\sigma_k^{2-} + \sigma_{z,k}^2}, \tag{11}$$

which determines the relative contribution of the measurement in the update of the estimate and is equivalent to the gain K_k introduced in Section 2.

The simulations were performed in the MATLAB environment, considering both static and dynamically varying measurement conditions by varying the measurement noise variance $\sigma_z^2(k)$.

In part of the study, normalized quantities are used. The normalization is performed with respect to a characteristic value of the coordinate, whereby both the coordinate and the corresponding variances are expressed in relative (dimensionless) units. This allows the results to be generalized independently of the specific image scale. For practical interpretation, the same relationships can be expressed in pixels $[px]$ and, accordingly, in $[px^2]$.

B. Effect of Noise Variance on Measurement Weight

In the Bayesian updating process, the weight of the measurement is determined by the coefficient w, introduced in (11). This quantity characterizes the relative contribution of the measured value with respect to the prior information in forming the estimate.

The dependencies of the weighting coefficient $w$and the normalized posterior estimate μ_k^+ on the measurement noise variance σ_z^2 are shown in Fig. 2a and Fig. 2b, respectively.

The figure shows a monotonic decrease in the weight $w$with increasing σ_z^2. For low values of the measurement noise variance, w approaches unity, indicating that the measurement has a dominant influence on the updated estimate. Conversely, as σ_z^2 increases, the weight decreases, reducing the influence of the measurement and increasing the role of the prior information.

The analysis of Fig. 2b shows that, for small values of σ_z^2, the posterior estimate μ_k^+ approaches the measured value, which is consistent with the high weight of the measurement. As the measurement noise variance increases, the estimate gradually shifts toward the prior value, reflecting the reduced influence of the measurement. This transition is smooth and continuous, ensuring stable behavior of the algorithm under varying measurement conditions.

This relationship provides a natural mechanism for adaptation to the quality of the measurement. For reliable measurements, the algorithm follows the measured values, whereas in the presence of strong noise, it automatically suppresses their influence.

Therefore, the weighting coefficient w can be interpreted as an indicator of measurement reliability, determined entirely by the ratio of prior to measurement uncertainty.

C. Effect of Measurement Noise on the Posterior Variance

The posterior variance σ_k^{2+} characterizes the degree of uncertainty of the obtained estimate and represents a quantitative measure of the reliability of the algorithm. An analysis of the variation of σ_k^{2+} as a function of the measurement noise variance σ_z^2 is presented below. This relationship is illustrated graphically in Fig. 3.

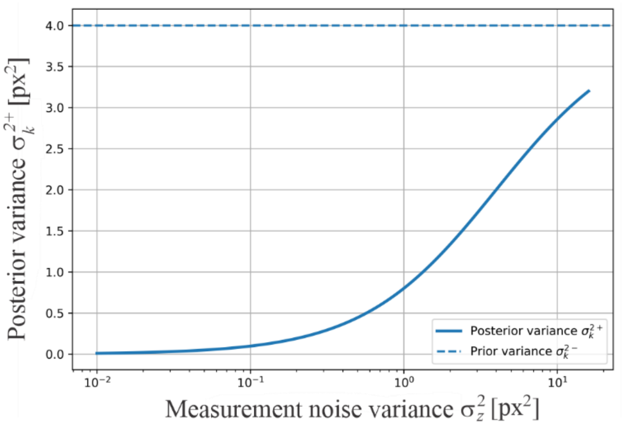


Fig. 3. Dependence of the posterior variance σ_k^{2+} on the measurement noise variance σ_z^2.

The figure shows that, for small values of σ_z^2, the posterior variance attains low values, indicating a high degree of confidence in the estimate. As the measurement noise increases, the variance grows and gradually approaches the prior variance, reflecting a decrease in the informativeness of the measurements.

A characteristic feature of the presented dependence is the presence of a clearly defined transition region, in which the increase of the posterior variance σ_k^{2+} becomes significantly more pronounced. This region corresponds to a range of values of σ_z^2 for which the ratio between the prior and measurement uncertainties changes substantially, leading to a redistribution of weight between the two sources of information. As a result, the algorithm transitions from a measurement-dominated regime to a regime in which the prior information exerts a dominant influence on the estimate.

This behavior is a direct consequence of Bayesian updating and provides a mechanism for preventing an unjustified increase in confidence in the estimate in the presence of noisy measurements.

Thus, the posterior variance can be interpreted as an indicator of the effectiveness of the algorithm under various measurement conditions, providing a quantitative assessment of the achieved improvement in accuracy.

D. Recursive Update of the Estimate in the Presence of Noise

Fig. 4 illustrates the recursive behavior of the proposed method in the presence of noisy measurements. The figure shows the true value of the coordinate, the measured values, and the posterior estimate μ_k^+, obtained through sequential Bayesian updating. The measurements are characterized by significant random deviations from the true value, reflecting the presence of measurement noise.

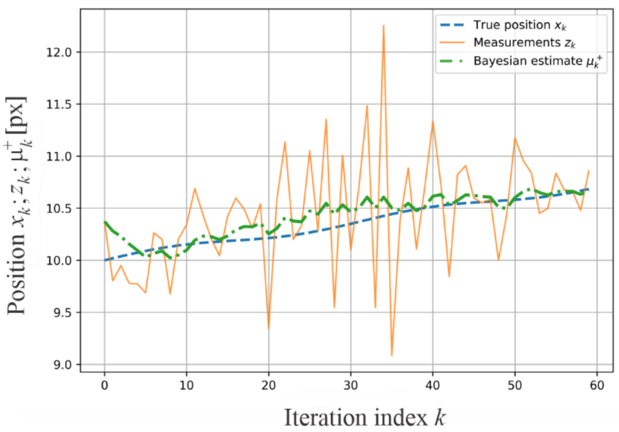


Fig. 4. Recursive update of the estimate μ_k^+ for measurements containing stochastic noise

Despite this, the posterior estimate smoothly follows the variation of the true value, effectively suppressing high-frequency noise components. This behavior results from the adaptive weighting between the prior information and the current measurement, realized through the coefficient w.

In the presence of abrupt changes in the measurements, the algorithm does not respond directly to instantaneous deviations but instead forms a stable estimate that reflects the overall trend of the process. Thus, effective filtering of noisy measurements is achieved without introducing an additional dynamic model.

The results demonstrate that the proposed approach provides reliable and robust estimation of the coordinate over a wide range of measurement conditions.

IV. Conclusion

This paper presents a Bayesian method for the recursive combination of prior and measurement information aimed at improving the accuracy of video-based measurements. The proposed approach is based on a probabilistic formulation of the estimation problem and employs an adaptive mechanism for estimating the measurement noise variance.

The main contribution of the study is the development of an adaptive scheme for estimating $\sigma_z^2(k)$, based on normalized innovation and a variable smoothing coefficient. This enables the algorithm to dynamically adapt to the current quality of the measurement information and to regulate the influence of the measurements in the estimation process.

Unlike classical approaches with fixed parameters, in which measurement reliability is assumed to be predefined, the proposed method evaluates it in real time based on the current data. This results in improved robustness under varying measurement conditions.

An additional advantage of the approach is that it does not require the introduction of an explicit dynamic model of the object motion. This makes it applicable in cases where the system dynamics are unknown or difficult to model, while still enabling effective suppression of noise-induced deviations.

The simulation results demonstrate that the proposed method provides more stable and reliable estimation compared to the direct use of measurements, while maintaining a consistent assessment of uncertainty through the posterior variance.

The proposed approach can be extended to multidimensional cases and combined with more complex models when necessary, making it a promising solution for applications in machine vision and object tracking systems.

ACKNOWLEDGMENT

The authors acknowledge the support of the European Regional Development Fund, within the Operational Programme "Research, Innovation and Digitalization Programme for Intelligent Transformation 2021–2027", through Project No. BG16RFPR002-1.014-0006 for the experimental investigations and measurement equipment, and through Project No. BG16RFPR002-1.014-0005 for the theoretical development and analytical framework of the study.

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