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Topic: Серверная система оценки данных лазерного гироскопа (Server based data estimation system for laser gyroscope)

Institution: Saint Petersburg Electrotechnical University (ETU)

Initial data (technical requirements): Experimental setup with laser gyroscope (RLG); papers about optimal Kalman filter.

Contents of the thesis: This report talks about the project of the development of a web application that would display data obtained from the laser gyroscope and filtered with Kalman filter and then displayed on a web client (web browser).

List of report materials: Introduction, Laser Gyroscopes, Kalman Filter, development of the web application, and a chapter on safety.

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SUMMARY

Explanatory note 46 p., 20 fig., 07 graphs, 17 sources.

The subject of the research (development) is: Development of a web application that displays Filtered data from Laser gyroscope.

The target of the GQW – The report contains a description about laser gyroscopes, Kalman filter and Web technologies used to display the data on a web client. The development of the application is done with the JavaScript language and uses the NodeJs runtime environment. The report also details background information about laser gyroscopes and filtering methods used to eliminate noise from the data obtained. Further the report contains the result of development, a fully functioning web app that is hosted on a web client (web browser) that displays filtered data obtained from the gyroscope through the serial port of a computer. The code processes the data and filters it and then broadcast it to the web client, finally the results and some explanations and comments.
АННОТАЦИЯ

Предметом исследования (разработки) является: Разработка веб-приложения, которое реализует алгоритм оптимального фильтра Калмана для лазерного гироскопа.

Цель выпускной работы – изучение принципов работы лазерного гироскопа, оптимальной фильтрации и использования современных интернет-технологий для отображения результатов эксперимента. Отчет содержит описание лазерных гироскопов, фильтра Калмана и веб-технологий, используемых для отображения данных на веб-клиенте. Разработка приложения выполняется с использованием языка JavaScript и использует среду выполнения NodeJs. В докладе также представлена справочная информация о лазерных гироскопах и методах фильтрации, используемых для устранения шума из полученных данных. В отчете приведены результаты разработки полностью функционирующего веб-приложения, размещенного на веб-клиенте (веб-браузере), который отображает отфильтрованные данные, полученные из гироскопа через последовательный порт компьютера. Код обрабатывает данные и фильтрует их, а затем передает их веб-клиенту, где они отображаются в текстовом и графическом виде.
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INTRODUCTION

Ever since the invention of lasers in the 20th century it has made a revolution in the fields of science and technology, the applications are numerous for the use of Lasers in today’s world, we can see it in being used to a significant extent in the fields of: science, medicine, commercial and industrial uses and even military application. Of the more prominent areas of application for Lasers is the use of lasers in measurement and metrology, and that coupled with the fact that Lasers have applications has application in geology, seismology, remote sensing; made the idea of a remote sensor using Laser technologies very tempting, and to do so the idea was to make use of ring laser gyroscopes because, The high sensitivity for rotations of large ring lasers along with their insusceptibility to linear translations makes the application of these instruments very attractive for studies of rotational signals from seismic events [1, 2]. The main idea is to develop a system that could send data from a gyroscope connected to a computer from a remote location via a network system, and that networking system is none other than the Internet.

The invention of the internet is arguably the most significant in human history [1], most certainly in modern times where it has changed, among others; the tele-communication and financial industries. It has come a long way from the old days where it was designed as a networking system during the cold war [4]. One of the more significant innovations that came with the internet are Open-source software (OSS), a type of computer software with its source code made available with a license in which the copyright holder provides the rights to study, change, and distribute the software to anyone and for any purpose [5].

In our work, we have used a filtration method called the Kalman filter for a better estimation of our data, Kalman filters are widely used guidance, navigation, and control systems of vehicles, especially aircrafts and spacecrafts.

The end result of our work is a system that obtains data from a laser gyroscope and filters that data in then broadcast it to a modern web client (web browser).
1. RING LASERGYROSCOPES

1.1. **Introduction and historical background**

A gyroscope is a word original to Ancient Greek γûros, "circle" and skopé, "to look" and is a device used to measure or maintain orientation and angular velocity. A spinning wheel or disc where the axis of rotation takes orientation in its own unaffected by the outer frame i.e. when it rotates, the orientation of the axis is unaffected by tilting or rotation of the mounting, according to the conservation of angular momentum. To put simply the rapidly spinning wheel will maintain its direction in space if the outside framework changes [6].

![Figure 1 – A mechanical gyroscope](image)

A gyroscope’ ability to keep its orientation in space has always made it very useful to be used in orientation and navigation, in the earlier days of gyroscopes it was used as a level, to locate the horizon in foggy or misty conditions.

The invention of lasers of the laser in the 1960s moved optical physics into a new level of precision and commercial applicability. One of the more interesting devices that the laser has made possible is the ring laser gyroscope [7]. The first experimental ring laser gyroscope was developed in the US by Macek and Davis in 1963 [8]. A ring laser gyroscope (RLG) is a ring laser that has two independent counter propagating waves that propagate through the same path; the difference in frequencies between the two beams according to the Signac effect is used to detect
rotation. The interference pattern between the counter propagating waves, results in motion of the standing wave pattern, which in turn indicates rotation.

![Ring laser gyroscope](image)

**Figure 2 – Ring laser gyroscope**

RLG has an active optical resonator which is the laser itself. If the gyro is rotated in the counterclockwise direction, the counterclockwise beam travels a shorter distance compared to the opposite beam.[9]

![Operational schematic of a ring laser gyro](image)

**Figure 3 – Operational schematic of a ring laser gyro**

**1.2. Principle of operation of a RLG**

At particular rates of rotation, a small difference in the time it takes for light to travel the ring in the counter directions is induced, according to the Sagnac effect. This creates a tiny separation between the frequencies of the counter-propagating beams, a movement of the standing wave pattern inside the ring, and thus a beat
pattern when the two beams are interfered from the ring externally. Therefore, the net shift of that interference pattern follows the rotation of the unit in the plane of the ring.

### 1.2.1. The Sagnac effect

Named after French physicist Georges Sagnac, the Sagnac effect was discovered in 1913 as a moving fringe pattern from an interferometer placed on a turntable [10].

![Figure 4 – Frequency shift in a rotating interferometer](image)

In a ring laser, two beams travel in counter directions around the ring cavity. The waves are reflected with the aid of mirrors. The enclosed area by the beam (the path) is \( A \). When the whole frame that the RLG is mounted on rotates with an angular frequency of \( \bar{\Omega} \), the difference in arrival time between the two beams is given by:

\[
\delta t = \frac{4\bar{\Omega}A}{c^2},
\]

where \( c \) is the speed of light; the relative phase difference between the beams that is caused by the rotation is:

\[
\delta \phi = \frac{8\pi \bar{\Omega}A}{\lambda c},
\]
where $\lambda$ is the wavelength; One approach to proves the Sagnac formula is with the use of Stokes’ theorem [11]:

$$f_{sagnac} = \frac{4\Omega A}{\lambda P},$$  

(3)

where $P$ here is the perimeter of the laser ring [12].
1.2.2. RLG Output linearization with Dithering

Even though RLGs are more accurate than mechanical gyroscopes, they suffer from a phenomenon called "lock-in" which happens at very slow rotation speeds. When the gyroscope is not rotating rapidly enough, the frequencies of the counter-propagating waves become nearly the same. In this case, crosstalk between the counter propagating waves can permit injection locking, so what happens is that the standing wave "gets stuck" in a preferred phase, therefore locking the frequency of each beam to each other rather than responding to gradual rotation.

One solution that is commonly used is forced dithering which can solve this problem reliably. The ring laser cavity is turned counterclockwise and clockwise about its axis using a mechanical spring whose frequency is set to the cavity’s natural resonance frequency. This makes certain that the angular velocity of the system is usually far from the lock-in zone. Typical frequencies are 400 Hz, with a peak dither velocity of 1 arc-second per second. Dithering does not remove the lock-in problem entirely, as each time the direction of rotation is back-pedaled, a short time interval exists where the rotation rate is near zero and lock-in can briefly happen. If a pure forced frequency oscillation is the case, these small lock-in times can accumulate. This was remedied by introducing noise to the 400 Hz vibration [13].

Figure 5 – Linearization through dithering.
2. KALMAN FILTERING

2.1. Overview of the Kalman filter

Named after Rudolf E. Kálmán, one of the primary developers of its theory; Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that is used to filter statistical noise and other imprecisions, with the use of a series of measurements observed over time, and it generates estimates that are more accurate than those based on single measurement, the estimated unknown variables are then used for estimating a joint probability of these variables for each timeframe.

The Kalman filter has multiple applications in many fields of technology. A typical application is for guidance, navigation, and control of vehicles, especially aircraft and spacecraft [14]. In addition, the Kalman filter is a broadly applied concept in the analysis of time series used in fields like signal processing and econometrics. Kalman filters also are of significant value in the field of robotic motion planning and automated control, it is even included in trajectory optimization sometimes. The Kalman filter also applies for the modeling central nervous system's control of movement. Due to the time delay between issuing motor commands and receiving sensory feedback, use of the Kalman filter provides a realistic model for making estimates of the current state of the motor system and giving updated commands [15].

In the figure below it is shown a loop where the Kalman filter holds the estimated state of the system and the uncertainty and variance of the estimation. The estimation is updated using a state transition model and measurement X of k which signifies the estimate of the system’s state at time step k before the k-th measurement yk been taken into account; P is the corresponding uncertainty.
The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. The algorithm is recursive. It can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required.

Figure 7 – Kalman Filter Recursive Algorithm.
Using a Kalman filter doesn’t suppose that all the errors are Gaussian [16]. However, the filter will give the exact same conditional probability estimate in the special case that all errors are Gaussian.

Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on non-linear systems. The basic model is similar to a hidden Markov models except that the state space of the Kalman variables is continuous and all of its observed variables have Gaussian distributions.

Kalman filter is a general and powerful tool for combining information in the presence of uncertainty [17].

2.2. Optimal Kalman filter for RLG

To combat errors, and in particular with random drift, a large number of different filters were proposed. Optimal in the linear class is a filter that realizes simple averaging of the signal. Nonlinear filters were also proposed, but it always turned out that they distort the signal in an unacceptable way. One way to deal with the random component of the error at present is to increase the duration of the observation. The error in measuring the angle increases in proportion to the square root of the time, and the error in determining the angular velocity falls according to the same law.

The considered method of filtration, being optimal, is still extremely inefficient. To increase the accuracy $N$ times, $N^2$ times more time is required.

Therefore, the problem of finding alternative ways to reduce the noise component of the RLG error, which does not require an increase in the measurement time, is of current interest. The solution of this problem would allow reducing the readiness time of inertial systems, increasing the speed of laser compasses and so on, while improving the accuracy of instruments.

The filtration of the white noise component of the drift is ineffective and, therefore, the methods of combating this error should be sought not on the methods
for processing the output signal of the gyroscope, but on ways of suppressing the conditions conducive to its formation.

At present, the optimal Kalman filter is the most effective among the others. The Kalman filter algorithm allows in real time to construct an optimal estimate of the state of the system, based on measurements containing errors; the measurement vector is regarded as a multidimensional output signal of a system burdened with noise, and the state vector is an unknown multidimensional signal to be determined. The condition for optimality of the constructed state estimate is the minimum of its mean square error.

The initial conditions on each new cycle of the algorithm are the estimation of the state of the system and the quantity characterizing its error. In the case of a scalar variable, such a characteristic is variance, which is the greater, the greater the scatter of individual values relative to the true one. A common variance estimate is the standard deviation, that is, the square of the standard deviation, which expresses the degree of spread of the quantity relative to the mean. A generalization of the variance for a vector, that is, a set of scalar quantities, is a covariance matrix. Its diagonal elements are the variances of the corresponding components of the vector, and the off-diagonal elements are the covariance characterizing the relationship between a pair of components. The set of measurements assigned to each of the instants of time, generalizes the measurement vector. The algorithm sequentially processes newly arriving measurement vectors, taking into account the values calculated on the previous cycle. In the next step, the initial conditions are refined by means of the measurements being processed on this cycle. For this, the algorithm calculates the weight of corrections to them based on the covariance matrices of the state and measurement estimates. The smaller the error is measured in comparison with the assessment of the state of the system, the more weight they will receive. The relative weights of the unknowns that determine the state vector of the system depend on the degree of their influence on the measurement vector: the greater weight will be received by those variables whose contribution to the measurements is greater.
The refinement of the initial conditions on the basis of the measurements entered in this cycle, in general, leads to a decrease in the uncertainty in the assessment of the state of the system. At the final stage of the algorithm's work, preparation for the arrival of a new measurement vector takes place. Based on the given linear transformation linking the subsequent state vector with the previous one, an estimation of the state of the system, referred to the time of the next measurement, is predicted. When constructing the covariance matrix of the predicted state vector, the Kalman filter takes into account the possibility of distortion of the model describing the behavior of the system by some random process with known statistical parameters. As the new measurements are processed successively, the filter accumulates useful information, so if the elements of the state vector are confidently expressed in terms of the measured quantities, the total error of estimates should decrease. However, since along with the improvement of the accuracy of estimates at the stage of their refinement, there is a decrease in the forecasting, these tendencies, compensating each other, will subsequently lead to a stabilization of the uncertainty characterizing the assessment of the state of the system.

With the help of the Kalman filter, we estimate the state of the discrete process, which we control, for a more accurate estimation of measurement errors. The evaluation process is based on the prediction of a system error at the time of the measurement $t$ of $k$ which is based on the optimal estimate $\hat{x}_k$ at the previous time of measurement. $x_k = F\hat{x}_{k-1} + W_k$. Let us consider a discrete linear equation describing the variation of the RLG parameters:

$$x_k = F\hat{x}_{k-1} + W_k ,$$

where $F$ is the transition matrix, $\hat{x}_k$ the n-dimensional state vector of the system, and $W_k$ is the r-dimensional vector of the input perturbation.

Input perturbations are assumed to be an r-dimensional discrete analog of Gaussian white noise with zero mathematical expectation and a known covariance matrix:

$$M[w_j w_k^\ell] = Q_k d_{j,k} ,$$

\(17\)
where \( Q_K \) is the covariance matrix of the system noise, \( d_{j,k} \) - the Kronecker symbol, which takes the value

\[
d_{j,k} = \begin{cases} 
1, & j = k \\
0, & j \neq k 
\end{cases}.
\] (6)

Part of the state vector is measured:

\[
Z_{k+1} = H_{k+1}x_{k+1} + V_{k+1}.
\] (7)

Here \( Z_{k+1} \) - m-vector of measurements, \( V_{k+1} \) - m-vector of measurement errors, \( H_{k+1} \) - (mxn) -matrix of measurements. The measurement errors are assumed to be an m-dimensional discrete analog of Gaussian white noise, for which

\[
M[V_{k+1}] = 0,
\] (8)

\[
M[V_jV_{k+1}^T] = R_{k+1}d_{j,k+1},
\] (9)

where \( R_{k+1} \) is a nonnegative definite matrix of dimension (mxm).

Measurement errors (otherwise measuring noise) and input disturbances (otherwise input noise) are uncorrelated: \( M[V_jW_k^T] = 0 \) for any \( j \) and \( k \).

The initial value of the state vector is assumed to be a Gaussian random vector with zero mathematical expectation, independent of the input perturbations of measurement errors: \( M[x_0W_k^T] = 0 \) for any \( k \).

The covariance matrix \( M[x_0x_0^T] = P_0 \) is a nonnegative definite matrix of dimension (nxn).

Based on the mathematical expectation of the object and the a priori information about the statistical characteristics of the input and measurement noise, and by measuring the part of the state vector, it is required to estimate the state vector so that the functional \( J \) takes a minimum value.

\[
J_k = M[(x_k - x_k^-)^T(x_k - x_k^-)] = \min.
\] (10)

The optimal estimate of the state vector is determined from an equation of the form

\[
x_k^\hat{} = x_k^- + K_k(z_k - Hx_k^-),
\] (11)

where \( x_k^\hat{} \) is a posteriori measurement estimate, \( z_k \) a measurement vector, \( K_k \) a filter matrix gain factor, \( H \) is a measurement matrix, \( (z_k - Hx_k^-) \) an updated sequence.
Based on the evaluation of the state vector and the object matrix, a forecast is made for the next step in calculating the estimate. At the same time, this forecast is corrected by using the updated sequence. The updated sequence is the sum of the forecast error and the measurement noise.

The filter gain matrix determines the weight with which the updated sequence is included in the estimation of the state vector. In the case of ideal measurements, i.e. when there is no measuring noise, the gain matrix is selected as the maximum. The greater the measurement noise, the less weight the updated sequence is taken into account when forming an evaluation of the state vector.

The Kalman filter has the form:

\[ x^\wedge_k = x^\wedge_k^- + K_k (z_k - H x^\wedge_k^-), \]  
\[ P^-_k = F P^-_{k-1} F^T + Q, \]  
\[ K_k = P^-_k H^T (H P^-_k H^T + R)^{-1}, \]  
\[ P_k = (I - K_k H) P^-_k , \]  

where \( P^-_k \) - the a priori covariance matrix of estimation errors, \( P_k \) - the posterior covariance matrix of estimation errors, \( I \) - the unit matrix.
3. DEVELOPMENT SETUP DESCRIPTION

This chapter describes the development of the web application for displaying the RLG data on the web client and the methods used to implement the Kalman filter in the designated environment.

3.1. Technical specifications of the RLG

This report deals with the work where a standard digital laser gyro “GL-1D” is used. The laser gyro is designed as a square shaped mono-block made of glass-ceramics and using the total internal reflection prism as reflectors. He-Ne active medium is excited by a high- frequency discharge. Data acquisition is carried out by double-surfaced photodetector followed by a two-channel amplifier. The Functioning of RLG supported by operation of auxiliary systems: the stabilization of power generation and stabilization of the perimeter. Operation of RLG at small angular velocities is ensured by means of mechanical dither - torisonal vibration of RLG around the axis of the resonator. This vibration is excited by piezoelectric actuators when an alternating electric signal with a frequency of 400 - 450 Hz is applied to them.

The main parameters for the RLG

- Scale factor (angular equivalent of one output signal period)
  \[ \Delta = 0.6561 \pm 0.0004 \, ^°/pulse \]
- Scale factor linearity \( 5 \cdot 10^{-5} \, (1\sigma) \)
- Scale factor stability \( 1 \cdot 10^{-5} \)
- Measurement range \( \mp 250 \, ^°/s \)
- Null shift stability \( \delta\Omega_0 = 0.005 \, ^°/h \, (1\sigma) \)
- Random walk \( R_\theta = 0.002 \, ^°/\sqrt{h} \)
- Communication interface RS422.
3.1.1. Description of the experimental setup

The block diagram of the installation is shown in Figure 8:

![Block diagram of the installation.](image)

Figure 8 – Block diagram of the installation.

1 - laser gyroscope GL-1D;
2 - optical gyro unit;
3 - electronic boards;
4 - two-channel oscilloscope;
5 - power supply;
6 - RS422 to RS232 interface converter;
7 - COM port of the personal computer;
8 – data acquisition software.

The laser gyro GL-1D is installed so that its sensitivity axis is directed to the zenith. The optical block of the gyroscope is connected with electronic boards, which ensure the functioning of gyro systems. Output signals of the gyro are observed on a two-channel oscilloscope. The gyro system is powered by a +5V, +15V, -15V power supply. Data transmission and reception in digital form, as well as control of the gyro systems is carried out via the RS422-RS232 interface converter and COM port of the personal computer by data acquisition software.

The device uses a digital laser gyro GL-1D, produced serially. The laser gyroscope is made in the form of a square monoblock with a prism of total internal reflection as reflectors. The active He-Ne medium is excited by a high-frequency dis-
charge. The information about the RLG rotation is collected by a two-site photodetector with a subsequent two-channel signal amplifier. RLG functioning occurs when auxiliary systems operate: power generation stabilization systems and perimeter stabilization systems. The RLG operation at small angular velocities is ensured by means of a vibrating support-torsional oscillation of the RLG resonator around an axis coinciding with its measuring axis, excited by piezoelectric propulsors when an alternating electric signal is applied to them with a frequency of 400 to 450 Hz. Management of gyro life support systems, processing and delivery of measuring signals is performed by a DSP signal processor, controlled by a microprogram stored in Flash memory, and also by a master control program from a personal computer. The main devices that process and generate signals are located in the Altera programmable logic chip. Data transmission to the computer and back is carried out using the device for receiving and issuing information via digital communication channels (RS422 port).

3.1.2. Algorithm for obtaining initial data

During the experiment, data sets were obtained with sample volumes (the amount of data in one array). The procedure for data processing consists of the following steps:

A. Elimination of gross errors (misses) in all data sets using the criterion $3\sigma$. It includes:

- obtaining an estimate of the mean value

$$\bar{N}_T = \frac{1}{n_T} \sum_{i=1}^{n_T} N_{Ti},$$  \hspace{1cm} (16)

- obtaining an estimate of variance $D_T$ and standard deviation $\sigma_T$

$$D_T = \frac{1}{n_T - 1} \sum_{i=1}^{n_T} (N_{Ti} - \bar{N}_T)^2,$$

$$\sigma_T = \sqrt{D_T},$$ \hspace{1cm} (18)
removal from the sample of gross errors \( N_{Tk} \) satisfying the relation

\[
|N_{Tk} - \bar{N}_T| \geq 3\sigma_T. \tag{19}
\]

After this, the procedure is completely repeated (here, the estimates are \( \bar{N}_T, D_T \) and \( \sigma_T \)) until all the data satisfy the criterion \( |N_{Tk} - \bar{N}_T| < 3\sigma_T \).

B. The weighted average RLG output frequency and the apparent rotation speed of the laser gyroscope are calculated according to \( \Omega' = \Delta v/K \), and the RLG shift of zero according to the formula \( \Delta N(T) = K\Omega T + K\Delta\Omega_0 T + \delta N(T) \) using

\[
\Omega = \Omega_E \cos(n,\Omega_E) = \Omega_E \sin \varphi,
\]

where \( \varphi \) is the latitude of the location of the installation; in St. Petersburg \( \varphi = 60^\circ \)

\[
\Omega_0 = \Omega' - \Omega_E \sin \varphi, \tag{20}
\]

where the value of the angular velocity of the Earth is \( \Omega_E = 15''/s = \frac{2\pi}{1296000} 15 \text{rad/s} \).

### 3.1.3. Measurement procedure

1) Zero drift

The magnitude of the drift of the RLG is usually determined by exposing the RLG measuring axis at a certain angle to the axis of rotation of the Earth. The error of the exhibition largely determines the accuracy of the measurement of the RLG drift. In the event that the measuring axis of the RLG is approximately orthogonal to the axis of rotation of the Earth, an exhibition error of 1’ gives an error in determining the drift of 0.004 °/ h. With the measuring axis of the RLG, approximately parallel to the axis of rotation of the Earth, the requirements for the accuracy of the exhibition are significantly reduced. In this case, an exhibition error of 1° gives an error in determining the drift of 0.002 °/ h. The RLG drift is determined by the following algorithm:

\[
\Omega_0 = \frac{N}{T} \frac{1.296 \cdot 10^6}{2\pi K} - \Omega_3 \cos(n\Omega_3), \tag{21}
\]
where \( N = \frac{1}{2\pi} \int_0^T \Delta \omega \, dt \) the number of periods of the output signal RLG, obtained during summation during the averaging time \( T \), \( \Omega_3 \) is the vector of the Earth's rotation speed; \( n \) is the vector of the measuring axis of the RLG. The scale factor \( K \) must be measured in advance. The multiplier \( \frac{1.296 \cdot 10^6}{2\pi K} \) is the angular price of the output RLG period, expressed in angular seconds. Since the angular second per second is equal to a degree per hour, expressing \( T \) in seconds, and \( \Omega_3 \) in degrees per hour, we get \( \Omega_0 \) in or in degrees per hour, or in angular seconds per second, which is basically the same thing. Which of these units should be chosen is determined from the averaging time \( T \).

2) Scale factor

This RLG parameter is determined by rotating the RLG with a constant speed and measuring the number of periods of the output signal in one revolution when rotating alternately in opposite directions:

\[
2\pi K = \frac{1}{2} (N^+_{2\pi} + N^-_{2\pi}), \tag{22}
\]

where \( N^\pm_{2\pi} = \int_0^{t_{\text{ob}}} (\Delta v)^\pm \, dt \), \( t_{\text{ob}} \) turnaround time, \( (\Delta v)^\pm \) the frequency of the output signal RLG when rotating in the positive or negative direction. The accuracy of determining the scale factor depends mainly on the accuracy of fixing the passage of the angle 2 rad (revolution). With a fixation error of 1", the relative error in measuring the scale factor is \( \sim 10^{-6} \). For a scale factor, the same characteristics are usually measured as for the RLG drift, but with one additional scale factor as a function of the rotational speed.

Modern RLG are characterized by relative instability of the scale factor at the level \( 10^{-6} \ldots 10^{-7} \).
3.1.4. Error Modeling of RLG

We are only interested in error model for a gyroscope with dithering mechanism because that’s the one used in our work. In our case RLG was used for angle measurements, so its mathematical model is:

\[ \alpha = \alpha + \varepsilon = \int [(1 + K)\dot{\alpha} + d]d\tau, \]

where \( \alpha = \int \omega dt \) is the RLG output signal.

Assuming that \( K \) – quasi-permanent and \( d \) consists of a gyro drift \( D_1 \), a drift gradient \( D_2 \) and stochastic noise \( w \), we obtain measurement errors:

Depending from angle:

\[ \varepsilon_{\alpha} = K\alpha. \]  

(24)

Depending form time:

\[ \varepsilon_t = D_1 t + \frac{D_2 t^2}{2} + \int w(t) \, d\tau. \]

(25)

So, the full angle measurement error can be written as:

\[ \varepsilon = \varepsilon_{\alpha} + \varepsilon_t. \]

(26)

The expressions above, describing the dynamic behavior of the error of the system, are written in the matrix-vector notation system as:

\[
\begin{pmatrix}
\dot{\varepsilon} \\
\dot{D}_1 \\
\dot{D}_2 \\
\dot{K}
\end{pmatrix} =
\begin{pmatrix}
0 & 1 & t \\
0 & 0 & 1 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
\dot{\alpha} \\
D_1 \\
D_2 \\
k
\end{pmatrix} +
\begin{pmatrix}
w_d \\
w_d \\
w_d \\
w_d
\end{pmatrix}.
\]

(27)

The system of equations above can be represented as:

\[ \dot{x} = Fx + w. \]

(28)

Its solution written down:

\[ x(t) = x\Phi(t, t_0)x(t_0) + \int_{t_0}^{t} \Phi(t, \tau)w(\tau), \]

(29)

where \( \Phi(t, t_0) \) is the transition matrix.
The evaluation process is based on the prediction of a system error at the time of the measurement $t_k$, which is based on the optimal evaluation $\tilde{x}(t_j)$ at the previous time of measurement:

$$x'(t_k) = \Phi(t_k, t_j)\tilde{x}(t_j). \quad (30)$$

The transition matrix for the gyroscope under consideration with $\Delta t = t_k - t_j$ and $\Delta \alpha = \alpha_k - \alpha_j$ has the form:

$$\Phi(t_k, t_j) = I + \int_{t_j}^{t_k} F \, dt = \begin{pmatrix} 1 & \Delta t & \Delta t^2/2 & \Delta \alpha^* \\ 0 & 1 & \Delta t & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}. \quad (31)$$

In the matrix, the measured angle increment $\Delta \alpha$ is used instead of an unknown error-free value; the difference between them in the evaluation process is negligible. The state vector will look like:

$$X = [\varepsilon, D_1, D_2, K]^T, \quad (32)$$

where $\varepsilon$ is the total error of the angle measurement, $D_1$ is the drift of the zero of the gyroscope, $D_2$ is the Gradient of drift, $K$ - instability of the scale factor.

The initial covariance error matrix $P_{k0}$ describes the uncertainty of the initial state of the system:

$$P_{k0} = \begin{pmatrix} \sigma_\varepsilon & 0 & 0 & 0 \\ 0 & \sigma_k & 0 & 0 \\ 0 & 0 & \sigma_{D_1} & 0 \\ 0 & 0 & 0 & \sigma_{D_2} \end{pmatrix}, \quad (33)$$

where for RLG:

$\sigma_\varepsilon = 5 \cdot 10^{-5}$" error in determining the angle;

$\sigma_k = 5 \cdot 10^{-5}$ quasi-constant component of rotation;

$\sigma_{D_1} = 0.005"/s$ - zero drift

The covariance matrix of the system noise $Q$ for small values of $\Delta t$ contains the following elements:

$$Q = \begin{pmatrix} r_\varepsilon^2 \Delta t & 0 & 0 & 0 \\ 0 & r_k^2 \Delta t & 0 & 0 \\ 0 & 0 & r_{D_1}^2 \Delta t & 0 \\ 0 & 0 & 0 & r_{D_2}^2 \Delta t \end{pmatrix}. \quad (34)$$
We take the values of the coefficients $r$ characterizing the device noise in accordance with each element of the covariance error matrix for the RLG:

\[ r_e = 5 \times 10^{-3}, \quad r_k = 5 \times 10^{-3}, \quad r_{D_1} = 0.5'' / s, \quad \text{and} \quad r_{D_2} = 0.2'' / s \]

Let us write down the covariance matrix of the measurement noise $R$ for angular measurements for the RLG:

\[
R = \begin{pmatrix}
5 \cdot 10^{-5} & 0 & 0 & 0 \\
0 & 5 \cdot 10^{-5} & 0 & 0 \\
0 & 0 & 5 \cdot 10^{-5} & 0 \\
0 & 0 & 0 & 5 \cdot 10^{-5}
\end{pmatrix}, \quad (35)
\]

In the case under consideration, we assume that the angle measurement noise is equal to the quasi-constant component of rotation.

The Kalman filter evaluates the entire state vector and suppresses the measurement noise. The estimate will be optimal if the a priori values of the matrices $Q$ and $R$, are chosen correctly. However, the optimal choice is possible only in the case when the characteristics of the processes are known exactly. In practice, such cases are extremely rare, so the matrix values are artificially overstated.

Transition matrix:

\[
F = \begin{pmatrix}
1 & \Delta t & \Delta t^2 / 2 & \Delta \alpha \\
0 & 1 & \Delta t & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{pmatrix}, \quad (36)
\]

In this matrix, the measured angular increment $\Delta \alpha$ is used instead of an unknown error-free value; the difference between them in the evaluation process is negligible.
The measurement matrix $H$:

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$  \hspace{1cm} (37)

In digital systems, the most common noise model is one of the varieties of the random process - discrete white Gaussian noise. This is a sequence of random numbers, each of which has a Gaussian probability distribution density with zero mathematical expectation and variance $D$. To model the realization of $N$ discrete samples of discrete white Gaussian noise, it is necessary to refer $N$ times to a sensor giving out independent random numbers distributed according to a Gaussian law with zero mathematical expectation and variance $D$.

As a model representing the noise of the system as a whole, we took a Gaussian random process with a correlation function of the form:

$$R(m) = De^{-am}. \hspace{1cm} (38)$$

Here $D$ is the variance of the process, and determines the correlation (statistical dependence) of the neighboring numbers (we assume $a > 0$). To simulate a Gaussian random process with an exponential correlation function, the following algorithm is used:

$$x(n) = k_1(n) + k_2x(n - 1), \hspace{1cm} (39)$$

$$k_1 = \sqrt{D(1 - k_2^2)}, k_2 = e^{-a}, \hspace{1cm} (40)$$

where $e(n)$ are the values of discrete white Gaussian noise with zero mathematical expectation and unit variance. Parameters of the model in this case are the variance of the output modeled process and the parameter that determines the statistical relationship of neighboring random samples.

As a rule, and in practice, the initial parameter is the normalized correlation coefficient:

$$\rho(1) = \frac{R(1)}{D} = e^{-a}. \hspace{1cm} (41)$$

This determines the normalized correlation of neighboring samples of the random process and is practically specified from the interval from 0.9 to 0.9999. When this
coefficient is equal to 1, then all values of the random process become the same, and when this coefficient tends to 0, it turns out - a discrete white Gaussian noise.

3.1.5. Results of Kalman filtering

During the experiments, we receive several arrays of data from RLG. After applying Kalman filter to data arrays (Fig. 9 - 12) we can see that filtering works correctly.

![Figure 9 – Result of Kalman filtering for data array 1](image-url)
Figure 10 – Result of Kalman filtering for data array 2
Figure 11 – Result of Kalman filtering for data array 3
Figure 12 – Result of Kalman filtering for data array 4
3.2. Environment for the development:

The development environment chosen for this project is NodeJs, and to use the Javascript programming language in the implementation of all the necessary estimation, acquisition and filtering techniques used in this report. NodeJs is a javascript runtime environment that is built on the google chrome’s V8 javascript engine, it is a lightweight and efficient and the package ecosystem, NPM, which Node uses, is the largest open source library in the world.

In our work we have used the serial port library “Serialport” that provides an interface for the low-level serial port streaming data and code necessary to control and obtain that data. We have also used the “ws” library which is an implementation of the WebSocket protocol for the server and web client implementation.

The app consists of a back end code to get the serial data and process it and apply Kalman filter to it then broadcast it to our web client, and front end code that works on the web client and listens to the data and display it in real time.

The code editor used is visual studio code (VScodo) which is an open source, free to use modern code editor from Microsoft.

The figure below is a representation of the working setup:

![Operational setup](image)

**Figure 13 – Operational setup of the work.**
3.3. development of the web application:

The first aspect of the web application is to get the data from the RLG with the help of the Serial port library.

Figure 14 – Application code for serial port communication.

Using some special commands, we can display the data on the command line interface:
Figure 15 – Unfiltered data received from the gyroscope.

We apply Kalman filter to it then broadcast it to our web client, for the purposes of visualization we use the `console.log()` command to display it on the command line interface:

Figure 16 – Filtered data from the Kalman filter.
Finally, we broadcast the data to our web browser and see the data. We have added a gauge to better visualize the data in the web browser and the gauge scales from 0 to 360.

![Gauge in web browser](image)

**Figure 17 – Application on a browser.**

In order to check that the connection is established and to see the data stream is possible to use the developer tools that are built in the browser:

![Developer tools in web browser](image)

**Figure 18 – Inspection of application on web browser.**
Using an outside graphing application, we can see the data visualized to give a better contract to the Kalman filtering; the data was selected randomly, and an equal amount was selected to give a coherent plot:

Figure 19 – Line plot of filtered and unfiltered random data arrays.

Figure 20 – Scatter plot for filtered and unfiltered random data arrays.
4. PROCEDURES REGARDING SAFETY ASSURANCE

To insure the safety of the work environment, many specifications and regulations must be adhered to, before starting an experiment, it's very important to think about what's the safest route to choose. Safety is of great importance that it is its own distinguished discipline called safety engineering. Safety analysis techniques depend immensely on the talent and experience of the engineer entrusted with safety analysis. In the last year’s model-based approaches became norm. Not in the same manner as old ways of safety insurance, model-based techniques derives relationships between causes and consequences from modals of the systems to the question of risk and safety.

Our work is reliant heavily upon the use of lasers, and to use lasers reliably and in a safe environment, one must keep in mind certain specifications relative to the use of lasers. A laser product may consist of a single laser with or without a separate power supply or may incorporate one or more lasers in a complex optical, electrical, or mechanical system. Typically, laser products are used for demonstration of physical and optical phenomena; materials processing; data reading and storage; transmission and display of information; etc. Such systems have found use in industry, business, entertainment, research, education and medicine.

There is a legal requirement to identify risks and take appropriate action to eliminate or control those risks (optical and non-optical). Users have a duty to protect both themselves and others from the potential hazards involved, particularly when working with the more powerful lasers. An assessment methodology is set out and the guide outlines measures to reduce hazards and check for adverse health effects. The assessment of non-optical hazards are dealt with by a number of different regulations which may be appropriate; for example, PPE Regulations, Workplace Regulations, Electricity at Work, and CoSHH (control of substances hazardous to health).
Laser Classes; Lasers are classified based on their potential for causing injury — especially eye damage, since the eye is most susceptible to excess laser light. There are four main classes for visible-beam lasers: Class 2, Class 3R, Class 3B and Class 4.

4.1. Manufacturing specifications regarding lasers

4.1.1 General specifications:
Laser products require certain built-in safety features, depending on the class to which they have been assigned by the manufacturer. The manufacturer shall ensure that the personnel responsible for the classification of laser products and systems have received training to an appropriate level which allows them to understand the full implications of the classification scheme.

4.1.2 Modification:
If the modification of a previously classified laser product affects any aspects of the product's performance or intended functions within the scope of this standard, the person or organization performing any such modification is responsible for ensuring the reclassification and relabelling of the laser product.

4.1.3 protective housing:
Each laser product shall have a protective housing which, when in place, prevents human access to laser radiation (including errant laser radiation) in excess of Class 1, except when human access is necessary for the performance of the function(s) of the product.

4.1.4 viewing optics:
Any viewing optics, viewport or display screen incorporated in a laser product shall provide sufficient attenuation to prevent human access to laser radiation in excess of the AEL for Class 1M, and for any shutter or variable attenuator incorporated in the viewing optics, viewport or display screen, a means shall be provided to:

A. prevent human access to laser radiation in excess of the AEL for Class 1M when the shutter is opened or the attenuation varied;
B. prevent opening of the shutter or variation of the attenuator when exposure to laser radiation in excess of the AEL for Class 1M is possible.

4.2. Laser Classification:

Class 1 and class 1M:
Class 1 and 1M lasers should not be viewed directly with optical devices such as binoculars and telescopes, other than that they don’t pose a real threat.

Class 2 and Class 2M:
Lasers that emit visible radiation in the wavelength range from 400 nm to 700 nm. class 2 lasers pose a threat on the eyes, protection from viewing of the laser beam is done by the natural avoidance of bright lights. class 2 lasers should not be stared at, i.e. you should not stare directly into the beam.

Class 3R:
Class 3R laser products are in the wavelength range from 400 nm to 1400 nm, direct eye contact with the laser beam should be avoided at all times. Wavelengths different from the specified laser range should be regarded as class 3B.

Class 3B:
A laser of type 3B is dangerous, and must only be used in a controlled laser area such as laboratory or other controlled areas where the hazards can be controlled. Exposure to class 3B beam should be avoided at all times.

Class 4:
Class 4 lasers are extremely hazardous and pose a real danger to the personal safety. Eye or skin exposure to direct or scattered exposure should be avoided at all times.
4.2.1. Radiation output standards:

Each laser product, except those of Class 1, should be described by a statement of the laser output’s maximum radiation, the pulse duration (if appropriate) and the wavelengths emitted. The name and publication date of the standard to which the product was classified should be included on the explanatory label or elsewhere in close proximity on the product. For Class 1 and Class 1M, instead of the labels on the product, the information may be contained in the information for the user.

The report deals with angular sensing with the use of a optical gyroscope. Proper working of these gyros is the key desirable feature. Impaired functioning of micro optical gyros can lead to serious safety issues while considering in making weapons and ballistic missiles since error in giving data of direction of rotation can create hazardous safety issues. The micro optical gyros which are currently being designed by our department is being followed by the International functional safety codes.

4.3. Protections against other hazards

The work environment is subject to risk not only from Lasers radiation and the risk it poses on safety and health, but also from other sources. The standards for safety when dealing with the equipment is that it shouldn’t impose a real threat when used in normal way (how it was designed to be used). Some of the sources of threat worth mentioning are:

Sharp edges:

All easily-touched parts of the equipment should be smooth and rounded so as not to cut and cause injury during normal use of the equipment. Conformity is checked by inspection and, if necessary, by application of an object that resembles a finger in size, shape and hardness, to check for abrasions or cuts.

Stability:

Equipment and assemblies of equipment not secured to the building structure before operation shall be physically stable.
If means are provided to ensure that stability is maintained after the opening of drawers, etc. by an operator, either these means should be automatic or there should be a warning marking to apply the means.

**Lifting and carrying:**

Equipment or parts having a mass of 18 kg or more should be provided with a means for lifting and carrying, or directions shall be given in the documentation.

### 4.4. The hazards involved

It is of great importance to take into consideration the full range of possible hazards and the conditions under which they could happen, taking into consideration the type of laser equipment (its class, the circumstances under which hazardous exposure could happen, and the kind of injury that could outcome) and the job or activity being performed. The most obvious hazard is the exposure of laser; however it is frequently not the only one. Any control measures already in set at the time of the risk evaluation will efficiently separate some of these hazards (except, perhaps, during servicing).

**The laser environment**

The laser environment covers:

- the site of the laser equipment, e.g., inner or outer of a structure within an enclosed and devoted laser working area; inside within a widely available or open-plan working area; outside;

- the working state area from an equipment viewpoint, e.g., the effect on equipment of temperature, humidity, vibration, dust etc. and the chance of disturbances or loss by crashes with people or moving equipment;

- The state of the working area from a personnel viewpoint, e.g., spacious or disarranged; clean or dirty; well-lit or dark; ease of use and ease of operation of the laser and associated equipment; the simplicity or complexity of the task being performed;
• The level of access, e.g., localized restricted area within premises having no public access; unrestricted area within premises having no public access; public access areas.

The people at risk:

Problems connecting persons at risk include how many of those at risk and if they are aware, protection and training. The people at risk can involve qualified and trained operators, service personnel, employees who may be unaware of the hazards, contractors, visitors, children and other members of the public who may not fully comprehend warning signs or value the dangers that may happen.
CONCLUSION

In the project detailed in this report, we have developed a web application using web technologies such as NodeJs; that is hosted on a web client i.e. a modern web browser that displays angular data obtained from a Ring laser gyroscope. The data is obtained through a serial port data stream interface that allows us to communicate and control the serial port of the computer, and then the data is filtered in real time, using an implementation of the Kalman filter which would give a less noisy new data stream, the new data stream is then broadcasted to the web client using the WebSocket communication protocol, an hosted on a webpage within the web client. The data is visualized by a graphical interface by an animated gauge that displays data in a more coherent manner.

The goals set before starting this project were accomplished and the project involved multiple technologies that needed to be comprehended fully, the web application is fully functional and can be used as a remote sensor or any other application that would utilize a remote access to the data stream.

Suggestions for the continuation of this work:
- Use other filtration methods to compare the performance of the Kalman filter and ultimately chose the best one.
- Keeping track of the data by logging it to a database with the designated timestamp.
- introduce functions that would trigger on certain events (data changes, sharp increase/decrease …etc).


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