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Sensor fusion applied to the estimate of luminous intensity (LUX) in practical class

Fusão de sensores aplicada à estimativa da intensidade luminosa (LUX) em aula prática

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ABSTRACT

In the last ten years, the development of sensors with greater accuracy and precision due to improvements in manufacturing processes has made it possible to expand their use in several areas. However, the acquisition value, especially of products from established manufacturers, in the face of their applications can make simpler projects unfeasible. The technique of fusion of sensor data presents itself as a viable alternative in the resolution of this question, because mathematical models can be proposed and used in various situations. These models allow you to improve the data obtained in order to generate reliable information. Thus, the objective of this work was to verify the performance of multiple linear regression applied to the fusion of redundant quantitative data from LDR 5 mm sensors in the estimation of light intensity (LUX) in simulated scenarios. To carry out the experiment, 3 LDR (Light Dependent Resistor) sensors, 3 LM393 signal conditioners, 1 USB 6009 DAQ data acquisition board (14 bits), 1 LT40 Extech luximeter, in addition to the LabView software, were used. It was found that the LDR A and B sensors showed higher levels of accuracy. In addition, it was found to mean improvement in the level of accuracy when combined the data from sensors A and B in the form of multiple linear regression.

RESUMO

Nos últimos dez anos, o desenvolvimento de sensores com maior acurácia e precisão devido a melhorias nos processos fabris tem possibilitado ampliação do seu uso em diversas áreas. Contudo, o valor de aquisição, principalmente de produtos de fabricantes consagrados, frente às suas aplicações pode inviabilizar projetos mais simples. A técnica de fusão de dados de sensores apresenta-se como uma alternativa viável na resolução desta questão, pois modelos matemáticos podem ser propostos e usados em diversas situações. Esses modelos permitem melhorar os dados obtidos a fim de gerar informações confiáveis. Sendo assim, objetivo deste trabalho foi verificar o desempenho da regressão linear múltipla aplicada à fusão de dados quantitativos redundantes de sensores LDR 5 mm na estimativa da intensidade luminosa (LUX) em cenários simulados. Para realização do experimento foram usados 3 sensores LDR (Light Dependent Resistor), 3 condicionadores de sinal LM393, 1 placa de aquisição de dados DAQ USB 6009 (14 bits), 1 luxímetro LT40 Extech, além do software LabView. Verificou-se que os sensores LDR A e B apresentaram maiores níveis de acurácia. Ainda, foi constatada significava melhora no nível de acurácia quando combinados os dados dos sensores A e B na forma de regressão linear múltipla.

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Introduction

As the technology of measuring quantities using sensing develops, the demand for accuracy and reduction of the costs of these sensors arouses the interest in methods that improve the quality of the data and present themselves as a reliable and necessary alternative to the treatment of information.

Methods based on the integration of data measured by various sensors are options for improving accuracy, such as sensor fusion. According to Anjos (2017), this technique uses more than one sensor of the same characteristic or not that extracts combined information increasing the accuracy of the measurement or supplying faults of each other. For the fusion of sensors a set of data is obtained and a correction model is applied to it and extracts its output, with the advantage of applying a technique of automatic diagnosis of failures, and in data acquisition by isolated sensor this process is done manually and time-consuming (Neves, 2017).

The fusion of sensors has been applied in several areas of knowledge due to its flexibility and precision. According to Yang et al. (2022) sensor fusion is able to improve the estimation performance of local measurements collected from different sensors, surpassing all estimates of a local state sensor. The deployment of sensor network systems extends the use of multisensor fusion, especially in decentralized systems where the cooperation of other sensors compensates for specific deficiencies such as missed detections and false alarms, improving accuracy and robustness in estimation (Li et al., 2019).

The fusion of this data is characterized by the aggregation and/or combination of various probability measures, and machine learning, statistics, estimation theory, and signal processing can be used, where combinations are products of various data sets that reduce uncertainty (Taylor & Bishop, 2019). Thus, algorithms used for fusion can be determined according to the type of information acquired and the characteristics of performance and operation of the sensors (Filho, 2007).

Given the availability of using the sensor fusion technique, several algorithms have been proposed such as kalman filtering (Sun et al., 2017), calculation of the “mean” on the information provided by sensors, thus including the weighted average (Zang & Wang, 2021), maximum probability estimation algorithm (Santana et al., 2018), likelihood function (Papa et al., 2019), fuzzy logic (Song et al., 2022) among others.

Thus, the purpose of this work was to verify the performance of the fusion of redundant quantitative data from Light Dependent Resistor (LDR) sensors in the estimation of light intensity (LUX) in simulated scenarios, applying adjustments and establishing statistical metrics by the multiple linear regression method.

Development

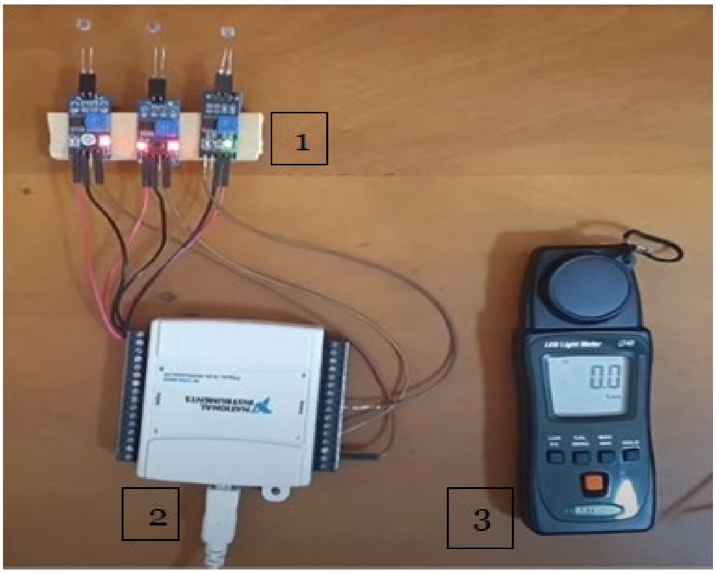
The experiment was carried out on 05/18/22 at the time reserved for the discipline of instrumentation and automation for agricultural systems in a synchronous remote class offered for the Graduate Program in Agricultural Systems Engineering of the Luiz de Queiroz School of Agriculture - Esalq, Piracicaba - SP.

Material and characteristics

To carry out the experiment were used 3 sensors of the Light Dependent Resistor - LDR type, circular format of 5 mm in diameter, response between 350 and 820 nm with maximum relative in the range of 530 to 580 nm, 3 LM393 signal conditioners, 1 DAQ USB 6009 data acquisition board (14 bits), 1 LT40 Extech luximeter, according to the system presented in Figure 1. Its technical characteristics (Datasheet) are described in table 1.

Figure 1.

Luminosity data acquisition system (LUX) through LDR sensors, LM393 signal conditioner, USB 6009 DAQ board and LT40 Extech luximeter.



Note: 1. Sensor and conditioner systems 2. USB 3.DAQ data acquisition card. Luximeter LT40.

Source: The authors.

Table 1.

Sensitivity, resolution and range of the components used in the experiment.

Device	Sensitivity	Resolution	Range
LDR 5 mm	±2.7 kΩ @ 10 lux	N/A	0.1 - 10,000 lux
LM 393	N/A	5% FSO	N/A
DAQ USB 6009	0,6 mVcc	14 bits	N/A
Luximeter LT40	± 3 % of reading	0.1 lux	39,999 lux

Source: The authors.

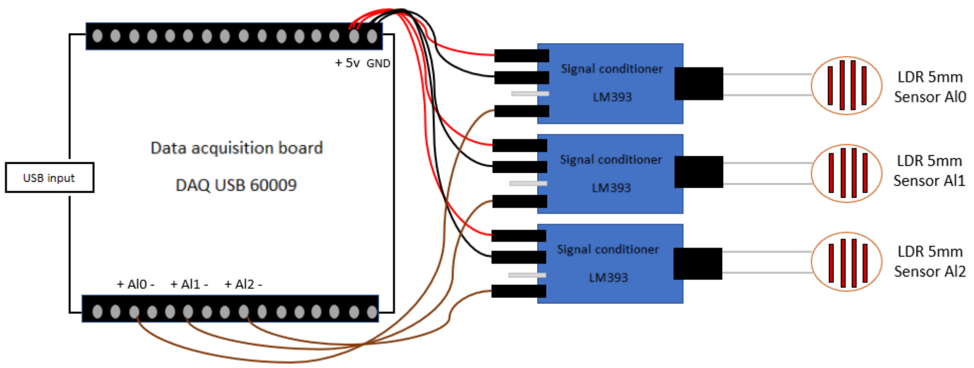
Operation and calibration process

For the operation of the system, the signal conditioners were connected to the analog ports available in the DAQ. These inputs are used to measure voltage variations of analog components that when measuring the quantity change the resistance and thus vary the voltage, being able to operate in infrared, visible and ultraviolet light bands. Each sensor has a resistance variation depending on the luminosity that is passed to the signal conditioner which in turn converts the resistance signal into voltage.

The outputs of the signal conditioners (red wires) were connected in a 5v port and powered by the same input (black wires) GND of the board, the signal wires of the conditioner (brown wires) were connected to the analog voltage ports, range 0 to 10 Vdc of the DAQ USB 6009, being them analog 0 (AI0), analog 1 (AI1) and analog 2 (AI2) as electrical diagram in figure 2.

Figure 2.

Representation of the electrical diagram of the experimental system of fusion of centralized. sensors.



Source: The authors.

To visualize the data, the LabView 2013 software (32 bits) was used, which presented amplitude values (v) of each sensor with a sampling rate of 5 Hz (five samples per second) and a resolution of 0.1 mVcc (minimum detectable variation). To verify the functioning of the sensors, the direct light was interrupted and at another time saturated in the receivers by means of a flashlight with LED emitter, with a temperature of 6500K.

In the measurement of the magnitude, the calibrated LT40 Extech luximeter was used, where it was also verified decreasing and saturating the luminous incidence. After this procedure, we went through the calibration process of the Lux curve, depending on the voltage generated by the sensor and the time, simulating low and high light scenarios in the same environment as all the components.

Were generated 12,036 data by the LabView software that were later transferred and treated in the excel environment for application of the sensor fusion technique by the multiple linear regression method.

Data Modeling

In order to establish the relationship between the voltage readings from LDR sensors and the luminous intensity recorded by the luximeter, regressive models combining such measurements were used. To this end, a set of 9 samples was used in this step, adjusting models for sensors A, B and C individually, and jointly. In this sense, linear, exponential, polynomial and logarithmic models were tested, prioritizing the choice of the model with the highest coefficient of determination (R^2) for each scenario.

To use the data from the different LDR sensors jointly, two strategies were explored. The first consists of calculating the arithmetic mean between sensor data A, B and C relating to the same reading for later conduction of the regression analysis. The second explores the redundancy of sensors through multiple linear regression, in which each LDR sensor represents a distinct independent variable (x), with selection of these variables through the stepwise method.

To verify the performance of the established models, an independent data set containing 7 samples was used. In this sense, values of luminous intensity were estimated from the established models using data from LDR sensors, which were compared in the form of linear regression with reference measures. To analyze the pre-established models, four regression metrics were considered: the coefficient of determination (R^2), mean error (EM), mean absolute error (EAM) and root mean squared error (RMSE). In fact, in regression problems it´s sought to select the model that refers values closer to the data, thus being the one that reduces the errors, this represented by the difference between the actual value observed and the value predicted by the model.

Results and discussion

From the pairing of the data recorded in the DAQ together with the readings made with the luximeter, it was possible to establish the relationship between the voltage values from the LDR sensors with the luminous intensity. This relationship is expressed by the mathematical models presented in Table 2.

Table 2.
Mathematical models obtained between data from sensors and reference values.

Y	X	n	R^2	Model
Lux	Tension (v) - Sensor A	9	0,999	Y=2732,2*exp(-2,071x)
Lux	Tension (v) - Sensor B	9	0,997	Y=2163*exp(-2,188x)
Lux	Tension (v) - Sensor C	9	0,990	Y=5292*exp(-2,167x)
Lux	Tension (v) - Medium sensor (A+B+C/3)	9	0,998	Y=3153,7*exp(-2,12x)
Ln (Lux)	Tension (v) - Sensor A (x_1) e B (x_2)	9	0,993	Y=(21,670*x_1)+(-24,098*x2)+4,789

Source: The authors.

When evaluated individually, the data from each LDR sensor are best represented from an exponential model with a descending format, reaching R^2 values higher than 0.99. Similarly, the model that combines the data from the three LDR sensors through an arithmetic mean also showed better adherence to the exponential model, with R^2 of 0.998.

When combining the data from the LDR sensors by means of multiple linear regression associated with the stepwise method for selection of predictor variables, it was verified that the data from the C sensor were not included in the model because they did not present significance in the statistical test (p-value > 0.05). Thus, the model obtained associates data from sensor A and B in the prediction of light intensity, presenting R^2 of 0.993.

The application of multiple linear regression, using stepwise method, favored the definition of the models and the rearrangement of combinations, because this method indicated the best predictors for inclusion in the analysis with emphasis on the resolution of the proposed problem, so the data from the C sensor were removed, thus contributing to less time of analysis and adjustments, lower requirement of computational processing, better performance in obtaining objective and clear results, without significant interference in accuracy and statistical metrics.

This technique has been widely used in modeling with the application of multiple linear regression with combinations of data, because the definition of predictors is related to the level of marginal significance in the statistical analysis with the predefined probability (p-value), but this technique does not always define the best adjustments of the variables (Akinwande et al., 2015), which did not occur in this study due to the observation of the best statistical metrics with the exclusion of the C sensor data in the combination with sensors A and B, indicated in stepwise.

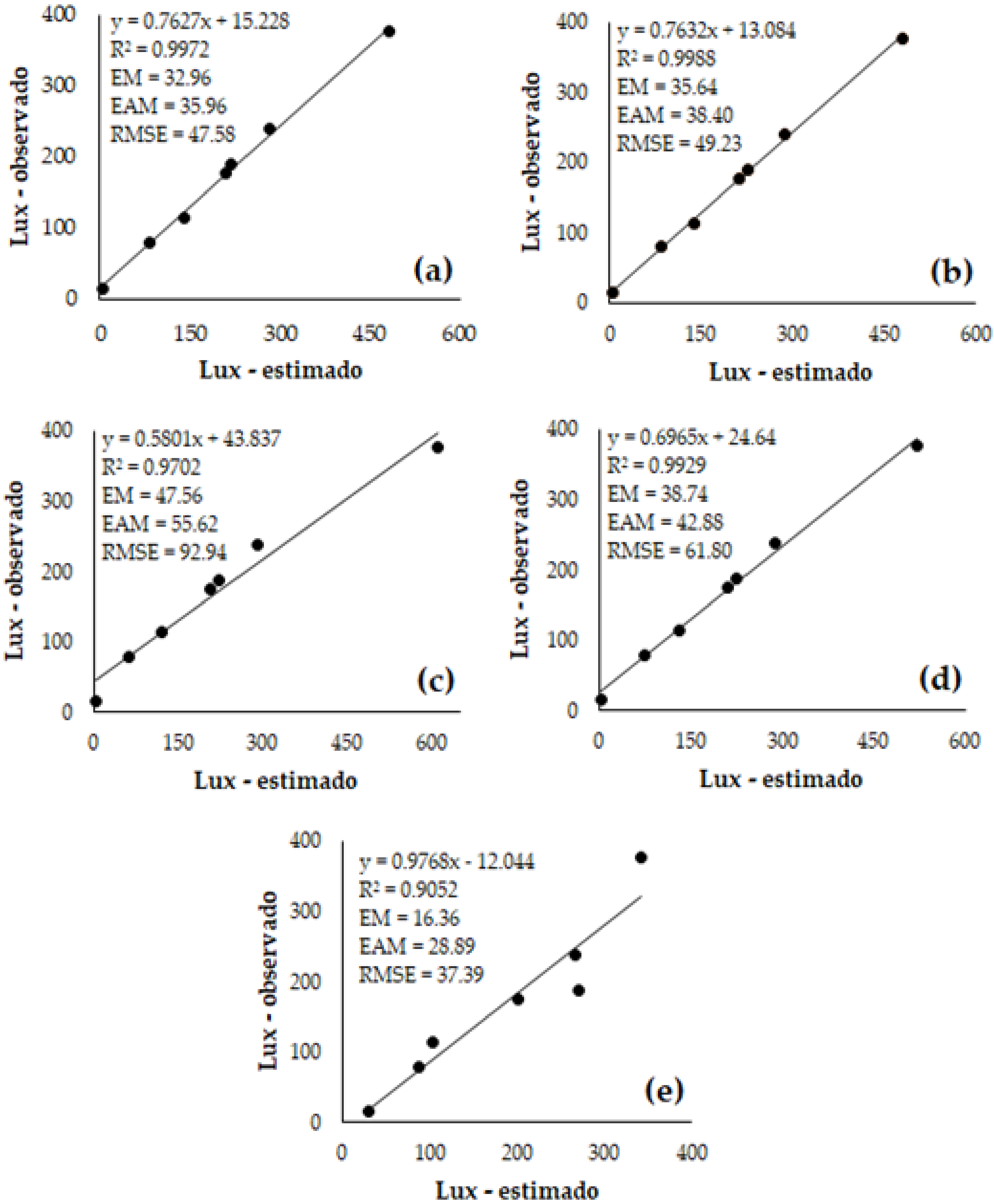
The insertion of many variables combined to determine the target attribute does not always provide better results, a factor observed in this study, confirming the importance of using the stepwise methodology for this type of analysis. Serrone and Moretti (2023), used adjusted multiple linear regression models to define environmental impact classes in clinker production and also applied the stepwise method to predict the independent variables where they selected the ones that most contributed to increased impacts within each class.

Another point that should be noted is that sensor C presented statistical metrics below sensors A, B and their combinations, being identified in the prediction analysis of input variables as non-significant. This fact may be related to a possible degradation of signal of this sensor, thus requiring observation evaluations of a historical database of records and real-time monitoring with applications of regression analysis. For Zang et al. (2023), the verification of continuous degraded signal flows in sensors is insufficient, in addition, in certain industrial environments the security of the monitored data needs to be preserved as to its privacy, which requires even more criteria in the analysis.

To verify the performance of the different models obtained, they were applied to an independent data set, aiming at the extraction of residues and inferences about precision and accuracy of the sensors. Figure 3 shows the graphs illustrating the estimated luminosity values from the LDR data in relation to the reference values, together with values of R^2, EM, EAM and RMSE.

Figure 3.

Relationship between light intensity data observed and estimated by mathematical models obtained from individual data from sensor A (a), sensor B (b), sensor C (c), and the association of data by arithmetic mean (d) and multiple linear regression (e).



Source: The authors.

The use of sensor fusion was also used by Santos (2020) to associate multiple sensors to achieve accuracy in a system for mobile robot location through the use of algorithm and the combination of odometry data. In their study, the mean of the linear and angular RMS errors reached, respectively, for the configuration with only the encoder, was 16.37 and 37.20, while the configuration with encoder, IMU and kinect, presented 2.17 and 3.63, showing the performance of the use of various sensors in the results through statistical metrics.

Li et al. (2022) used the fusion of acoustic emission signals and photodiode for the purpose of monitoring selective laser fusion in-situ quality. The multi-sensor fusion method presented significantly increased the accuracy of the classification due to a slight increase in computational time compared to single-sensor based methods.

When evaluating the residues related to the individual models of each sensor, it was verified that sensor A presented greater accuracy, with RMSE of 47.58 lux, followed by sensor B and C, with RMSE of 49.23 and 92.94 lux. When the sensor data were combined in the form of an arithmetic mean, the accuracy was reduced, reaching an RMSE of 61.80 lux.

According to Santana et al. (2018), they developed a system to locate a mobile robot placed indoors. And from simulations in Matlab, they obtained results in which the fusion was able to moderate the cumulative errors at the point determined by the odometry, and also to increase the tolerance of the disturbances in the position of the robot.

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Finally, by applying the model obtained by multiple linear regression, it was possible to achieve the best results in terms of accuracy, with RMSE of 37.39 lux. This result is due to the exclusion of data from sensor C, which presented substantially lower performance than sensor A and B.

Conclusions

Based on the experiment carried out, it was possible to verify the functioning of the LDR sensors together with signal conditioning and data recording devices, as well as to verify the behavior of the response signal in the face of variations of light intensity in the environment.

Also, from the use of a luximeter, different mathematical models were obtained relating the voltage recorded by the LDR sensors and light intensity.

When applying the models obtained, it was verified that the LDR A and B sensors presented higher levels of accuracy. In addition, it was found to mean improvement in the level of accuracy when combined the data from sensors A and B in the form of multiple linear regression.

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