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Machine learning enhanced optical distance sensor

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ABSTRACT

Presented for the first time is a machine learning enhanced optical distance sensor. The distance sensor is based on our previously demonstrated distance measurement technique that uses an Electronically Controlled Variable Focus Lens (ECVFL) with a laser source to illuminate a target plane with a controlled optical beam spot. This spot with varying spot sizes is viewed by an off-axis camera and the spot size data is processed to compute the distance. In particular, proposed and demonstrated in this paper is the use of a regularized polynomial regression based supervised machine learning algorithm to enhance the accuracy of the operational sensor. The algorithm uses the acquired features and corresponding labels that are the actual target distance values to train a machine learning model. The optimized training model is trained over a 1000 mm (or 1 m) experimental target distance range. Using the machine learning algorithm produces a training set and testing set distance measurement errors of <0.8 mm and <2.2 mm, respectively. The test measurement error is at least a factor of 4 improvement over our prior sensor demonstration without the use of machine learning. Applications for the proposed sensor include industrial scenario distance sensing where target material specific training models can be generated to realize low <1% measurement error distance measurements.

1. Introduction

Machine learning [1,2] involves the use of past experience to optimize the performance of a particular algorithm. It is quickly establishing itself as an important tool in a number of applications including financial markets, self-learning robots, speech recognition, computer vision and remote sensing [3–7]. Machine learning is also increasingly being deployed in the optics domain, for example, in camera systems where device-independent RGB colour information is estimated using a regularized polynomial machine learning model [8], in spectroscopy where a Support Vector Machines (SVM) based algorithm is used to classify different types of steel [9], and in optical systems where the Modulation Transfer Function (MTF) is estimated by feeding experimental data into a Support Vector Regression (SVR) based algorithm [10]. Furthermore, in optical communications, various machine learning techniques are being deployed as part of the signal processing algorithms to tackle various incoming optical signal properties such as amplitude and phase noise [11,12].

In this paper, to the best of the authors' knowledge, presented for the first time is a machine learning enhanced optical distance sensor which uses camera acquired multiple images of a target illuminated spatially varying coherent laser beam spot produced by control of an ECVFL. A regularized polynomial regression based supervised machine learning algorithm [1,2,13–16] is deployed in our previously proposed ECVFL-based distance sensor design [17] where the ECVFL current is controlled to change the size of an laser spot that strikes the target sensing zone. Images of the varying target plane beam size are used to extract features used to train the deployed supervised machine learning algorithm. This unique correspondence between the set of target illuminated beam sizes acquired at a certain target distance with the known target distance value is exploited effectively in the machine learning based operation of the demonstrated distance sensor. Compared to the previous demonstration of our sensor [17], this paper introduces a number of key innovations. In Ref. [17], an imprecise geometric optics based model is deployed which uses the acquired laser spot size data to give an intermediate distance measurement that is far from the actual distance value. Using the intermediate measured and actual distance values, a Two Dimensional (2-D) calibration plot is curve-fitted which is referred to for classification of targets at unknown distances. Firstly, this method has no guarantee of convergence. Secondly, the use of the intermediate step introduces further sources of error as it involves an additional curve-fitting operation.

In this paper, a regularized polynomial regression based machine learning algorithm is deployed which uses a single greater than two

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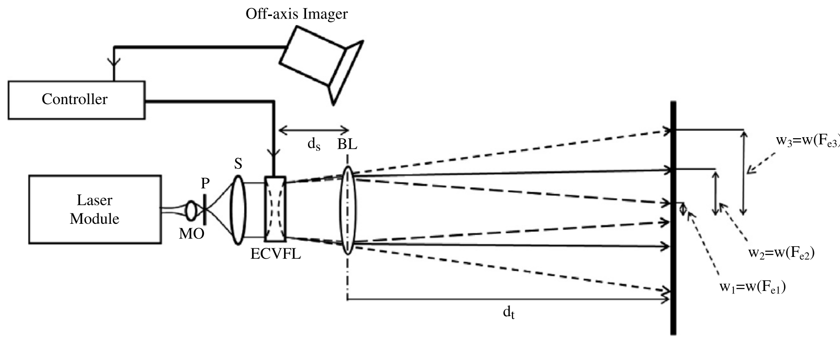

Fig. 1. Design of the ECVFL-based optical distance sensor.

parameter mapping function which maps the features acquired from the data to a distance measurement. In this paper, well established regression algorithm techniques are deployed to train a machine learning model with optimized parameters for lowest testing set errors possible. Furthermore in Ref. [17], 100% of the acquired data is used for training as well as testing purposes and thus the resulting maximum error value is likely an underestimate of the error of the distance measurement system. In this paper, 60% of the acquired data is denoted as the training set and the remaining 40% is denoted as the testing set. The resulting testing set error is a more realistic error of the sensor system. In addition, the algorithm deployed in Ref. [17] is based on the geometrical optics model which requires an initial distance "guess" to begin an iterative procedure and that initial guess was provided by the Max–Min–max mode of the sensor system [18]. In this paper where a machine learning based algorithm is deployed, there is no need for an initial starting value for the sensor operation.

The rest of the paper is arranged as follows. Section 2 gives an overview of presented sensor design and its operations. Section 3 is the experimental section and gives details of the proof of concept demonstration which involves machine learning sensor operations, experimental results, and a discussion on practical aspects of the technique. A conclusion at the end of the paper summarizes the findings. An Appendix section is also added that gives a description of the deployed regularized polynomial regression machine learning algorithm.

2. Machine learning enhanced optical distance sensor

Fig. 1 shows the hardware design of the proposed machine learning enhanced distance sensor. Light from a laser module entering a Microscope Objective MO is focused onto a Pinhole P before being collimated by a collimation lens S. The collimated beam passes through an ECVFL and a Bias Lens BL, separated by a distance d_s, before striking a target at distance d_t from the BL. The ECVFL is driven by a current i_e which corresponds to an ECVFL focal length F_e. The target illuminated spot is viewed by an off-axis imager, which has a customized field of view sufficient to cover illuminated targets over a chosen application range. Both the imager and the ECVFL are operated from a single Controller platform, such as a laptop computer. In each of the camera acquired images, the area covered by the laser spot (in pixels) is denoted as x.

The basis of the machine learning enhanced sensor operation is as follows. At a fixed d_t plane, n number of images are acquired, each having a different i_e value and a corresponding x value. This is repeated for m d_t planes, where each plane is separated by fixed separation Δd_t. All the acquired x values are arranged into a matrix $\mathbf{X}$ of dimensions $m \times n$ such that $\mathbf{X}$ is given by:

$$\mathbf{X} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & x_3^{(1)} & \cdots & x_n^{(1)} \\ x_1^{(2)} & x_2^{(2)} & x_3^{(2)} & \cdots & x_n^{(2)} \\ x_1^{(3)} & x_2^{(3)} & x_3^{(3)} & \cdots & x_n^{(3)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ x_1^{(m)} & x_2^{(m)} & x_3^{(m)} & \cdots & x_n^{(m)} \end{bmatrix}, \tag{1}$$

where $x_j^{(i)}$ is the beam spot area (in pixels) of the jth image at the ith target plane, and $i = 1, 2, \ldots m, j = 1, 2, \ldots n$. "$(i)$" is written in bracket form to indicate that it is not the mathematical operation of the power, but only used as a superscript. Note that from a machine learning point of view, the columns of $\mathbf{X}$ represent n features and the rows represent different training examples. Additionally, the m target planes constitute the labels $\mathbf{y}$ where $\mathbf{y}$ is an $m \times 1$ matrix:

$$\mathbf{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ y^{(3)} \\ \vdots \\ y^{(m)} \end{bmatrix}, \tag{2}$$

where $y^{(i)}$ is the target distance d_t value at the ith target plane, and $i = 1, 2, \ldots, m$. The regularized polynomial regression hypothesis function $\mathbf{h}$ is given by (see Appendix):

$$\mathbf{h} = \mathbf{X}\boldsymbol{\theta}, \tag{3}$$

where $\mathbf{h}$ has dimensions of $m \times 1$, and $\mathbf{X}$ is the modified feature matrix for polynomial regression (see Appendix): See the equations in Box I.

A complete derivation of the above Equations is given in Appendix. The objective of the algorithm is to find the optimum parameter matrix $\boldsymbol{\theta}$ which allows Eq. (3) hypothesis function $\mathbf{h}$ to effectively predict distance values for a given feature matrix $\mathbf{X}$ and corresponding labels $\mathbf{y}$. In order to optimize $\boldsymbol{\theta}$, first a cost function J($\boldsymbol{\theta}$) is utilized which is deployed as part of the regularization based polynomial regression algorithm and is given by (see Appendix):

$$J(\boldsymbol{\theta}) = \frac{1}{2m}\left[\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)^2 + \lambda \sum_{j=1}^{n}\theta_j^2\right], \tag{6}$$

where λ is the regularization parameter. Next, using Eq. (10), the gradient descent algorithm to find the training parameter matrix is as follows (see Appendix):

Repeat until convergence:

$$\left\{ \begin{aligned} \theta_0 &:= \theta_0 - \alpha\frac{1}{m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)\cdot x_0^{(i)} \\ \theta_j &:= \theta_j - \alpha\left[\left(\frac{1}{m}\sum_{i=1}^{m}\left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)\cdot x_j^{(i)}\right) + \frac{\lambda}{m}\theta_j\right] \\ &\text{where } j = 1, 2 \ldots n \end{aligned}\right\}. \tag{7}$$

Once the trained model parameters, i.e., the elements of the $\boldsymbol{\theta}$ matrix are obtained using the gradient descent algorithm, the testing phase involves acquiring x data for unknown target distances which is used to predict respective distance values using the optimized hypothesis function $\mathbf{h}$ from Eq. (3). The next section gives a step by step description of the experimental steps involved in the machine learning enhanced optical distance sensor operations.