Image-based water level estimation for redundancy information using convolutional neural network

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Abstract: Monitoring and management of water level has become an essential task in hydroelectric powers. Activities as water resources planning, supply basin management and flood forecasting are mediated and defined through its monitoring. The measuring station is located on the Madeira River in Rondônia, Brazil. The measurements are made by sensors installed on the river facilities that carry out the estimations precisely. Weather conditions influence the results obtained by these sensors; therefore, it is necessary to have redundant approaches besides the sensors which maintain the high accuracy of the measured values. Conventional cameras supply this necessity measuring it through human eyes. However, its method is not reliable and has low accuracy. It is proposed an approach, in redundancy to sensors, to use image processing to measure the water level, with high accuracy, and to predict the water level measured using a convolutional neural network for regression. Results present low errors according to its prediction.

Keywords: *Hydroelectric Power Plant, Energy, Water level, Redundancy information, CNN*

1. INTRODUCTION

Monitoring water level has become an essential task for the regulatory control of rivers in order to manage disaster risk assessment, flood warnings, water resources planning, public and industrial supply. In hydropower energy production, it is essential to monitoring the rainfall, inflows and water level in order to maximize the energy revenue, while taking into account dam safety risks [1]. The continuous monitoring of inflows and water level is an essential tool for hydropower dam operators by providing real-time data for decision making in power generation and planning. This information, which is highly valuable, requires a maximum accuracy and must be efficiently available to the hydropower control systems and operators.

The inflow and water level monitoring techniques have become more advanced over the years in response to increased demands for more accurate, timely and reliable information [2-4]. Different methods are used in redundancy in order to safely guarantee the availability of this information. Staff gauge, installed at hydrometric stations over the river, is the most used and the simpler tool for water level detection and observation. Therefore, a water level monitoring system can be composed of sensors and video cameras for the staff gauge, which measures the level of the water at the control room. However, in days of storms or climate changes, the sensors used may not be accurate presenting flawless in the acquired data [5]. Moreover, video cameras pointed at the staff gauge, used as a secondary method of measurement, are monitored by human eyes. The problem with this method is that human eyes are not reliable and subject to errors, which compromise the security of the system. Therefore, defining an accurate and reliable method to monitor the water level is a challenge for hydropower system control.

Predictive models based on a dataset of previous measurements provide an ideal solution to monitoring the water level and streamflow in hydrology. Methods using Artificial Neural networks [6,7], Support Vector Machines [8,9] and hybrid models [10,11] have been discussed to predict water level and streamflow. In common, they use measurements from sensors of meteorological and hydrometric stations. However, such methods applied to safe and accurate monitor water level at hydropower control remain an open field of research. To that end, this study proposes to develop an automatic detection approach that can be used in redundancy of sensor techniques, in order to assure a security system of monitoring water level. It proposes image analysis techniques and neural networks in order to automatically measure and predict the water level considering images from conventional cameras of the staff gauge.

The dataset used as a case study was provided by the Jirau Hydroelectric Plant, installed on the Madeira River, in the state of Rondônia, Brazil. It consists of real time videos of the staff gauges at different time lapsing (day and night) and weather conditions (sunny, cloudy, and raining). Digital image processing is applied to remove noises for better visualization, and to extract the region of interest of the staff gauge. Therefore, it is possible to determine the water level measurement, creating a relationship between the water line surface and the beginning of the staff gauge. Convolutional neural networks (CNN) with a regression layer is applied to train and predict the water level. The Jirau plant is managed by the Consortium Energia Sustentável do Brasil (ESBR).

2. CASE STUDY

Dataset

The dataset consists of thirty-five videos in real time of the staff gauges between 05/31/2020 and 06/04/2020 during different moments, days, nights, and weather conditions. These videos are separated into frames, totaling 3.364 images, and the water level is measured for each image obtained. Initially, is removed from all images the symbol of date and hours preparing it for the extraction of the region of interest. Detected the water level, these data are prepared to be trained by a CNN Regression, thus, each image is classified by its level and divided in two sets: 2.706 images for training set and 658 for testing set.

Image Processing

Image processing consists of enhancing the image in order to extract ROI. In most of the images, the camera angle is not suitable, and the staff gauge looks not straight which makes it complicated to detect the water level in the final analysis. Moreover, the image quality also influences the extraction of the ROI, as depicted in Figure 1(a). To improve image quality, a vertical shearing filter is applied to make the image straight [12]. Next, the non-uniform illumination is corrected by applying imaging segmentation. The morphological opening filter is applied to noise reduction and gamma filter to enhance the contrast. The resulting image is depicted in Figure 1(b). To extract the

ROI, the enhanced image is binarized and the borders of the ROI are detected and cropped from the image. The result is the region of interest of the image and it is depicted in Figure 1(c).

(a) *(b)* *(c)*

Figure 1. (a) Original Image, (b) Image Enhancement, (c) Extraction of the region of interest

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Water level detection

The staff gauge contains count marks which correspond to the level of the water reached. To measure the water level, it is necessary to define a window size of these count marks, in pixel coordinates, and obtain the number of counts present in the staff gauge. The water level is obtained through the image obtained by the extraction of the region of interest. The staff gauge is made up of counters that mark the value at which the measurements are. Thus, it is necessary to define the window size of these counters in pixel coordinates and obtain the number of counters present in the staff gauge. In addition, the size difference between the beginning of the ruler and the river's surface line is also defined. Considering a fixed mark, in meters, the number of counts and the defined surface line, it is possible to obtain a relationship between them according the Eq. [1]:

$$l = r - \left(c + \frac{d}{s}\right) * 0.1 \tag{1}$$

where l is the water level of the river, r is the fixed mark, c is the number of counts on the staff gauge, d is the difference between the water line surface and the beginning of the staff gauge and s is the size of each counter in pixel coordinates. To ensure the results are in centimeters, l is multiplied by 0.1

Convolutional Neural Networks model proposed

The proposed CNN model is composed of 19 layers in which the first layer is responsible to normalize the image dimension in order to guarantee the output of 224 rows and columns and the three channels (RGB). The next five layers contain a set of filters in order to perform convolutional operations with its subsequent layer. For the set of filters, each of them produces an activation map which is stacked along the depth dimension, producing the output volume. As a parameter it is used for all layers, a kernel with size 3x3. To avoid fast reduction of matrix dimension it is set padding 0 after each convolutional layer. For each layer non-linearity layers involve the use of a nonlinear activation function which takes a single number and performs a fixed mathematical operation on it, and it is a complement of the convolutional. Rectified linear units, ReLu, is the most popular and to be non-saturating is the fastest to apply the convergence of gradient descent. It computes the activation function f(x), where x is the output from the convolutional layer and the input of reLU Eq. (5) which means that its activation is threshold at zero [11].

$$f(x) = max(0, x) \tag{2}$$

The pooling layer is responsible to reduce the spatial size, the number of parameters and the computation in the network. It was used an average pooling type to reduce the activation maps. However, it was necessary to apply a dropout layer equal to 20% in order to decrease furthermore the data. The fully connected layer performs classification of the features and extracts all the convolutional layers [20]. To perform the predictions, a regression layer is added at the end of the CNN architecture. The CNN architecture proposed is summarized in Figure 2. It represents the six convolutional layers with its respective filters between brackets, the reLU and average pooling layer (after each convolution layer), one dropout layer, the fully connected layer and the regression layer to make the predictions.

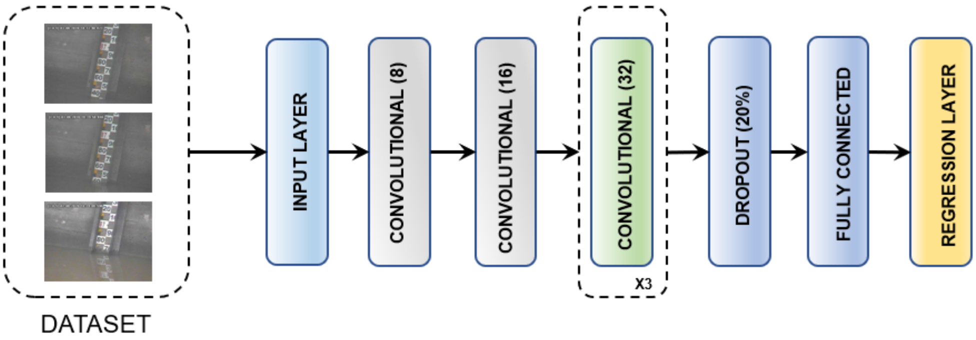

Figure 2. Convolutional Neural Network architecture

The proposed predicted model is evaluated by three different criteria: the root mean square error (RMSE), depicted by Eq. [8], the mean absolute error (MAE) in Eq. [9] and the determination coefficient (R^2) in Eq. (10),

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \qquad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \qquad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y})^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (4)$$

where Nis the amount of data, ŷi predicted value, yithe measured value and yi the average of the measured value. These errors are used to measure the accuracy of the prediction model for training and testing. The RMSE and MAE measured the magnitude of the errors. A lower value for RMSE is better than a higher one. The MAE calculates the average over the data set between the prediction and the water level measurements. R^2 represents the relationship between the variance of prediction and the total variance of data

3. RESULTS AND DISCUSSIONS

The proposed model is evaluated by training and testing images for the CNN Regressions predictions. Table 1 shows the results of RMSE, MAE and R^2. As can be seen, the accuracy for training images predictions was 93%, while for testing images was 91%.

Table I. Evaluation of the prediction

Dataset	RMSE	MAE	R^2
Training	0.2668	0.1991	0.9004
Test	0.2829	0.2228	0.8868

Figure 3 shows predictions where Figure 3(a) correspond to the training dataset and Figure 3(b) the testing dataset. The proposed model is able to produce results close to real measurements on training and testing dataset.

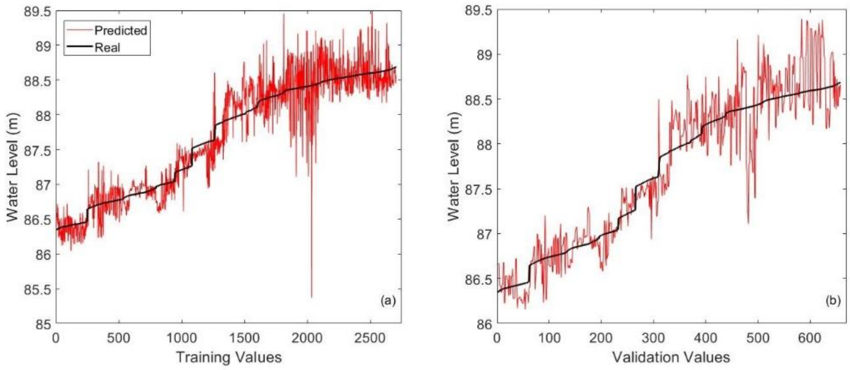

Figure 3. (a) Training Prediction, (b) Testing Prediction

4. CONCLUSIONS

This work proposes water level detection using images in a strategy based on a CNN model. This model was trained and tested using an image dataset extracted from videos of the measuring rule provided by Jirau HPP. The predictive capacity of the proposed model was tested in terms of RMSE, MAE and R^2, resulting in low errors for training and test sets. Therefore, it can be concluded that CNN based strategy is a promising approach for water level detection of Madeira River, and can collaborate with security regarding data integrity, through the redundancy of information through another acquisition paradigm. This safety is essential in the efficiency studies of Jirau Hydroelectric Power Plant and energy production as well as hydropower control and management. For future works, it is necessary to study other configurations of the neural network and other deep learning strategies to improve the generalization of the model.

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