The use of Computer Vision and Pattern Recognition in Condition Monitoring of Pelton Runners

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Abstract:

In the present paper we will show you how Computer Vision can help powerplant operators to obtain better and more reliable runner inspection results and therefore can save maintenance costs.

Condition monitoring and predictive maintenance are trends that penetrate industrial sector and consequently also the hydro business. This paper introduces a new approach of component monitoring by using Computer Vision and Pattern recognition to automate the inspection of Pelton runners.

For this reason, the concept foresees to install an image acquisition unit with an industrial camera and light sources in the turbine casing. The automated system then takes images of the buckets in regular intervals and does assessments and geometrical measurements on the images.

In addition, in a case study it could be shown that Machine learning algorithms and Pattern recognition are capable to detect and even classify cavitation erosion.

The gained experience from the pilot installations shows that such a system can be beneficial for electric utilities as the inspection results are more reliable and less dependent on the skills of the expert. This is very interesting for operators that act internationally as the needed know-how is not everywhere available. In addition, neither an outage of the unit is needed, nor the opening of the casing is necessary. Thus, the unit remains available for the dispatcher at all the times. All in all, the system can contribute to significant cost savings for the operation and maintenance (O&M) of hydro units.

1 Introduction

Condition monitoring is today a frequent buzzword in the industry. In different sectors it is already a well-established tool for optimizing maintenance and thus increasing efficiency and profitability of the equipment.

In this regard hydropower is no exception and several electric utilities started with the development of such expert systems [1], [4]. Most of the systems are based on sensor data already available at site on SCADA. However, with this information the condition of the equipment (e.g., a Pelton Runner) can only be assessed indirectly. To judge the hydraulic surfaces of a bucket profile a visual inspection is needed. For this task, the turbine casing needs to be opened and the scaffolding installed to grant a good access to the runner. The inspector does a visual examination of each bucket, marks and defines the size of irregularities and takes pictures for the reporting. Such a process is expensive, time consuming and the quality is very much dependent on the skills and experience level of the expert. The inspection result is thus not in any case reproduceable.

On the other hand, in recent years the developments in Computer Vision made big progress and concepts such as pattern recognition by means of neuronal networks are becoming state of the art. With this background it is a logical step to apply this new option in technology on the above-mentioned inspection task to improve the reliability and reduce costs.

2 Method

2.1 Concept

The concept of the present automated inspection system consists of two main steps. Firstly, the automated acquisition of images of each bucket of the runner. In a second step the postprocessing and analysis of these images. The two process steps are working independently but do exchange information via a central storage or database where the pictures are saved (Figure 1).

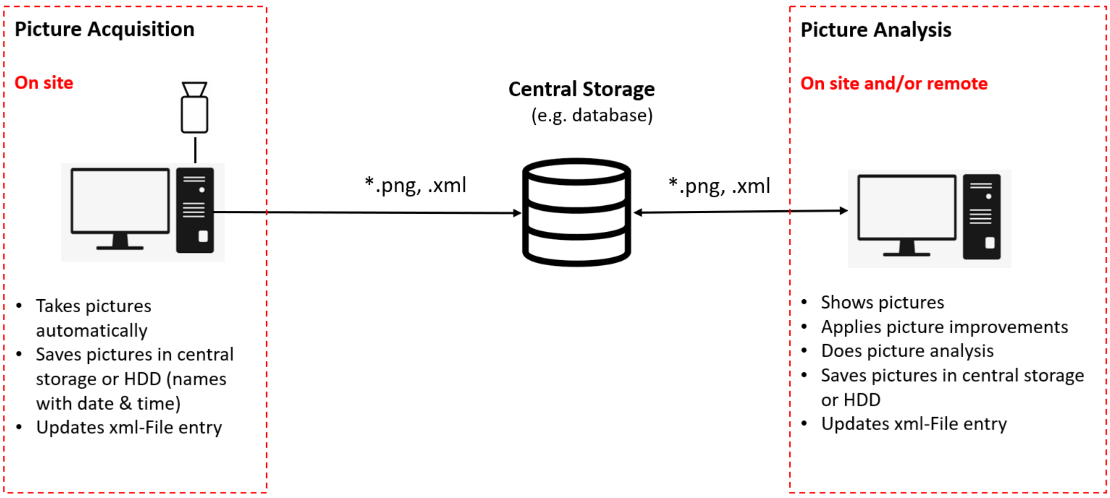

Figure 1: Concept and data flow of the Inspection system

2.2 Image Acquisition

It is part of the concept that the acquisition of the images is done with the runner in rotation. In our case the turbine is ramping down after closing of the injectors and disconnection of the generator from the grid. This boundary condition makes it necessary that the industrial camera has good dynamic properties and allows a time controlled and external triggered exposure.

In Figure 2 the concept for the image acquisition is shown in detail. The industrial camera (3) is in radial direction to the outer diameter of the runner. This allows a good view into the buckets of the runner (1). On each side of the camera two light sources (8) are located. The intensity of the light is adapted to the very low exposure time that is required due to the dynamics of the scene. The whole image acquisition process is managed by a controller (4). This controller measures via impulses from a proximity probe (7) the rotational speed and gets the actual circumferential position. With these values the delay period of the trigger is calculated to get an image of the selected bucket.

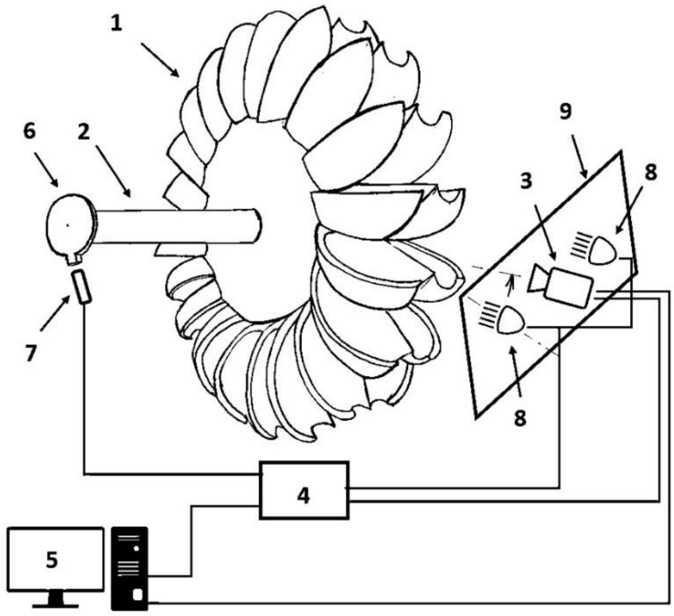

Figure 2: Schematic drawing of the image acquisition device

2.3 Conventional Image Analysis

To extract information from the images there is a pre-processing needed which contains image improvement operations such as illumination corrections, histogram equalization or special colour filters. Based on the optimized images, geometrical data or other information can be derived. In the following, two examples of image analysis procedures are described. But many more are possible depending on the specific needs of the operator or maintenance team.

2.3.1 Splitter width measurement

The aim of this analysis is to measure the width of the splitter edge from an image. This allows to quantify the damage on a bucket due to erosion. Based on earlier measurement or model calculations the efficiency losses can be estimated.

The steps of this measurement operation are shown in Figure 3 below. From a given image (a) a region of interest (ROI) around the area of the splitter edge is extracted (b). In a next step the colour space of the image is mapped to grey values (c). With the application of a binary thresholding operation (d) the top of the splitter edge gets visible in white. To measure the splitter width, the width of the white band can be extracted at any position. Finally reference lines at the location of the initial width of the splitter edge can be added to visually support the erosion quantification (e, f).

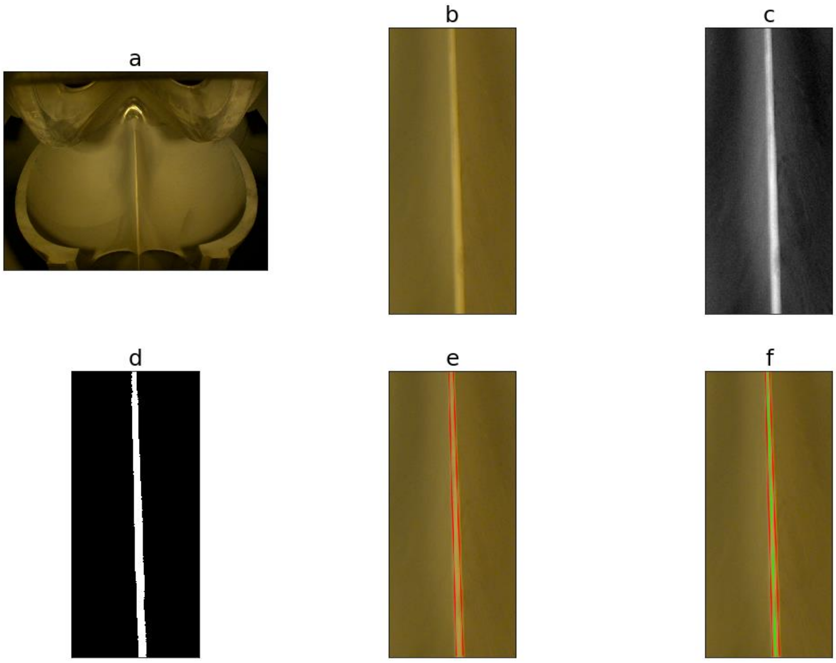

Figure 3: Process steps of the splitter width measurement

2.3.2 Pose Estimation

In Computer Vision the pose of an object refers to the relative position and orientation of the object to the camera [2], [3]. It can be changed by moving resp. rotating the camera or the object relative to each other. Pose estimation is an image operation that allows to correlate the 2D (planar) data of an image with the 3D information of a given real scene or object. The output is the relative position between camera and object.

In the present application, pose estimation is used to link features such as edges, curves, or section cuts of a known 3D bucket profile (e.g., from CAD model) with the image of a bucket taken by the inspection system. This allows drawing of reference lines and other characteristic features into the images (called Augmented reality, AR).

To calculate the relative position a set of references is needed. In case of the Pelton bucket the template markings on the bucket top area are used.

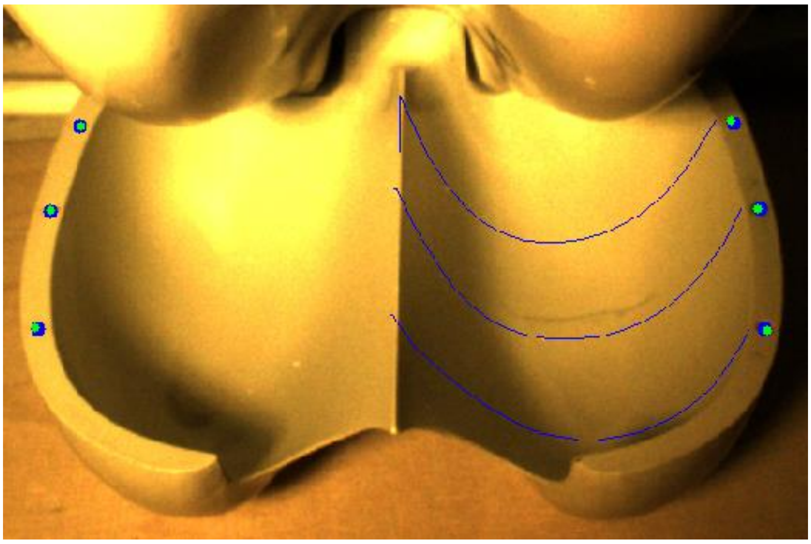

Figure 4: Pose Estimation with added template cross-section lines

In Figure 4 above the use of pose estimation is illustrated on a sample bucket. At the rim of the bucket the markings are the positions of the profile templates that were used to calculate the alignment. Based on this information, the template cross section lines were added in the right bucket half. With these added references a damage in the bottom of the bucket can be better located in 3D space.

2.4 Erosion Classification by means of Machine Learning

To investigate the possibilities regarding erosion classification from images by Machine Learning, a feasibility study was performed with inspection images taken manually as input. This research is the baseline for an implementation with a mounted camera system as shown above which takes photos at a defined shutter speed, exposure time and constant lighting.

Figure 5: Position and detail image of the cavitation damage on cut-out lip

2.4.1 Image pre-processing

In the present case the goal was to classify the intensity of cavitation erosion that occurs on the back of the buckets near the cut-out lip (see Figure 5). Since there is an individually grading of cavitation for the left and right bucket halves, pre-processing was needed to separate the two halves. For this reason, a pre-processing pipeline was developed to fulfil this task.

As conventional edge detection algorithms (as found in computer vision libraries as OpenCV) did not work properly to separate the bucket from the background, a semantic segmentation with the U-Net-approach was implemented as first step. The second step was to create bounding boxes for the separation of right and left bucket, followed by the last step which uses the adapted Rubber Sheet Model to unwarp the region of interest in the cut-out from bended shape (elliptical shape) to create a rectangular image (see Figure 6).[5]

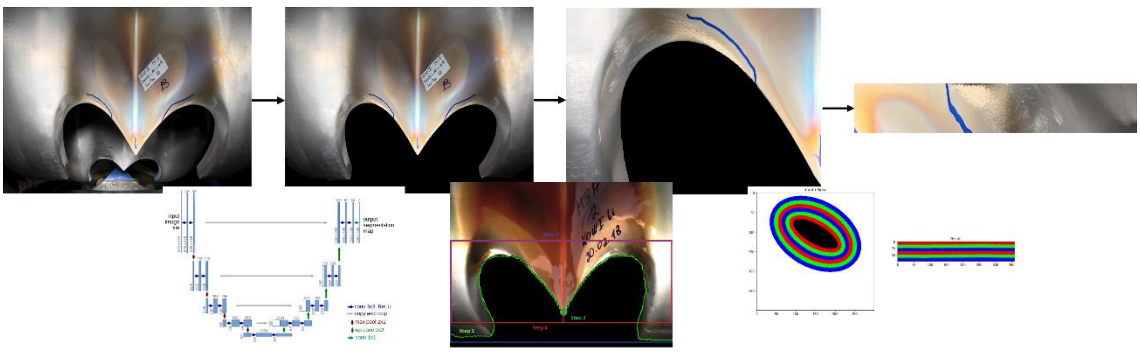

Figure 6: Pre-processing: Background removal, separation of halves, unwrapping

2.4.2 Erosion Classification

Two different methods regarding erosion classification where evaluated. Texture classification with Local Binary Patterns extraction (LBP) together with a k-nearest neighbour classifier (k-NN) and a Convolutional Neural Network (CNN). To benchmark the two methods, images were manually classified by an amateur and an expert into classes from no cavitation to strong cavitation resp. Class 0 to Class 4 (see Figure 7)

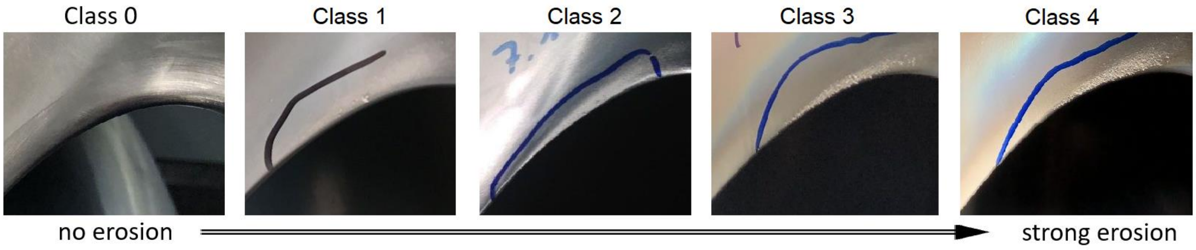

Figure 7: Classification of erosion intensity from class 0 to 4

The dataset for the experiments consisted of approximately 4000 bucket halves.

The first method uses a Local Binary Pattern (LBP) extraction algorithm to get more information about the local texture. The idea behind was to receive a measurable value that is correlated to the pattern resp. porosity of the hydraulic surface which is affected by cavitation erosion. In a second step this extracted information is then assigned to the above shown classes by a k-nearest neighbour classifier.

The second approach makes use of a Convolutional Neural Network (CNN). In this method the Convolutional Layers of the network learn how to extract features from the given images (bottleneck features). These features are used in the later layers of the network to fulfil the classification into the five classes (0-4).

3 Pilot Projects

3.1 Installation

The pilot instrumentation of the system has been done in a Swiss powerplant. In the meantime, a second installation in Austria has followed. Both units are Pelton turbines unit with horizontal axis. The first unit gets its water from a catchment area in the alps where a glacier is present. Therefore, the sediment load in summer is rather high and the runner sees some sand erosion over the time of operation.

In Figure 8 the image acquisition unit can be seen. The camera with a resolution of 2048x1536 pixels (Austria: 4505x4505px) at the center plane of the runner and the two LED light sources on each side are mounted above the injector. With this position a good view into the bucket and thus to the hydraulic active surface is granted. In addition, with this installation location the equipment is well protected against the heavy forces of the splashing water during operation.

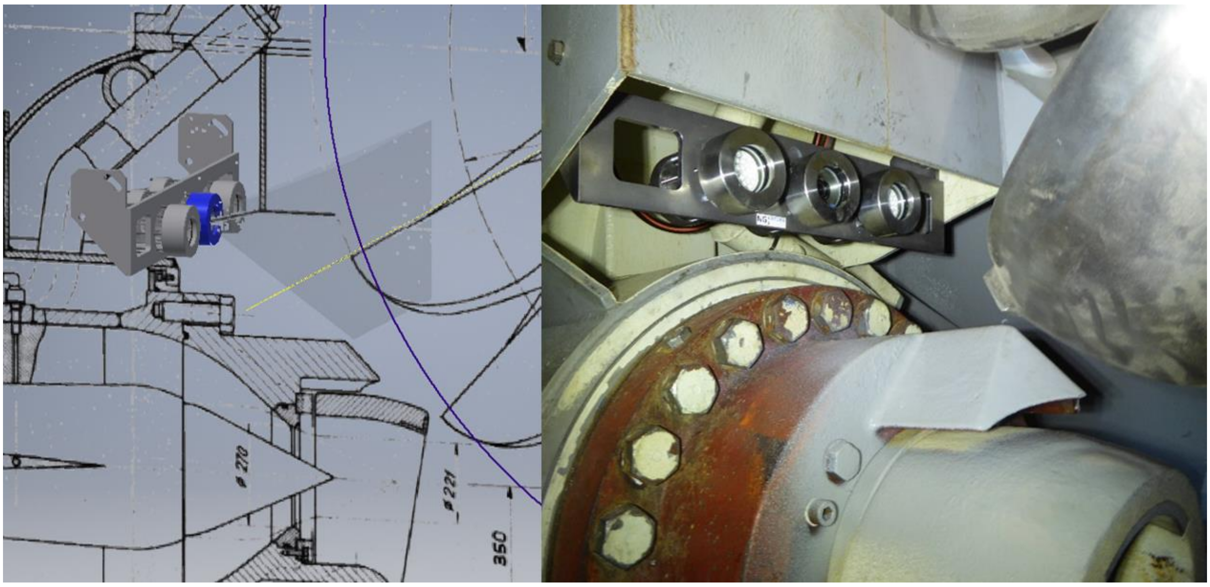

Figure 8: Image acquisition unit of the Swiss pilot project in CAD (left) and installed at site (right)

3.2 Results

The system has been in operation for two years now and takes images independently. Since the unit is operated as a peak load supplier it is started once or twice daily and is then in operation for a few hours. The installed system configuration is set in a way that every time the unit is taken from the grid and the runner speed is ramping down a set of images is taken. A sample image of one bucket taken by the pilot system during commissioning is shown in Figure 9.

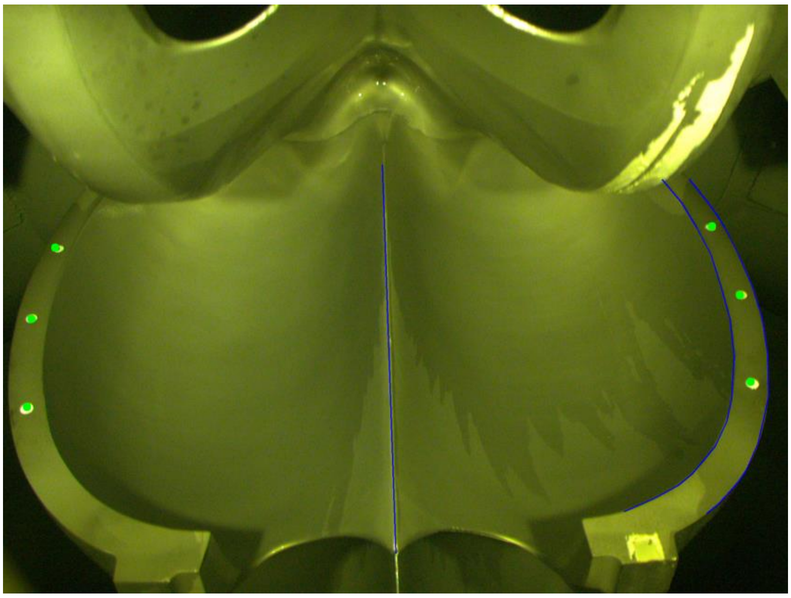

Figure 9: Sample image of bucket 11 taken with the pilot installation incl. AR projections

The main outcome from the first months of operation is that all further analysis is strongly dependent on a good quality of the images. To get high quality images several points need to be considered.

Firstly, the lens needs to be clean and free of any droplets. This can be achieved by a cleaning process that applies oil-free pressurized air to the lens of the camera casing to blow away the drops. If the water contains a high amount of sediments and especially sediments with high hardness values (> Mohs 7) a chemical hardened glass or even a sapphire glass is strongly recommended to avoid visual disturbances due to fine scratches in the lens over time.

A second point is that motion blur due to the rotation of the bucket should be minimized. The selection of a sufficient low exposure time can tackle this problem. But by knowing the dependency between light sensitivity of the camera, exposure time and illumination of the scene one gets to the conclusion that this is only possible with the selection of a sufficiently strong light source.

For the further tasks of postprocessing and analysis of the images, the basic algorithms are implemented but will be further optimized with the increased amount of sample images that are available from the pilot installation.

3.3 Erosion Detection and Classification

Despite of the subjective classification of the erosion intensity by humans, and too many classes the CNN approach performed well on all five classes (baseline is 20% for guessing). The lower results of the human contestants and the LBP approach shows that the CNN has learned a strong feature representation from just 4000 images (see Table 1)

Method	**train/test**	**Accuracy**
LBP + k-nearest neighbors	3324/434	32.03%
Xception Light (CNN)	8960/434	58.29%
Human Amateur	100/50	48%
Human Expert	0/50	36%

Table 1: Results of the erosion classification for all methods tested

The results for a binary classification between class 1 and 4 (see Figure 7), shows even better results (see Table 2). With an accuracy above 97% the Neuronal Network (CNN) can with a very high probability decide whether cavitation is present or not on the pictures taken by the system. Class 1 vs. class 4 was chosen instead of class 0 vs. class 4 to avoid misleading results regarding the applied cavitation markings.

Method	**train/test**	**Accuracy**
LBP + k-nearest neighbors	1204/122	77.05%
Xception Light (CNN)	3584/122	97.54%

Table 2: Results of the erosion classification between class 0 and 4

4 Discussion

The results of the present installations prove that the concept is viable and can support the O&M divisions of turbine operators. The recent developments in Computer Vision and the availability of powerful Computer Vision libraries made such a new approach for runner inspections possible.

It seems clear that with the concept at hand various external negative effects can be reduced and therefore quality is increased in numerous ways:

- The result is **independent on the skills and experience level of the expert** who is normally doing this inspection manually. The system is always applying the same clearly defined and given parameters.
- With a permanently installed light source the illumination is always the same. This **reduces misinterpretations** due to optical biases.
- In remote locations experts are not always available. Therefore, with such a system travel cost of professionals at electric utilities that act worldwide can be reduced.
- Due to its computerized assessment of the images **automated reports** can be generated that are **always up-to-date and available from any remote location** that has access to the network.
- As no dismantling of casing parts and installation of any scaffolding is needed, there are **no labour costs** for these tasks.
- The **availability of the unit is always given** as the system is permanently installed in the casing. Consequently, it is not needed to plan an outage for an inspection and the dispatcher can at any time decide to start the unit.

From the experience of the pilot installation, there is still a big potential for improvements and further developments. But the first results are very promising and prove the feasibility of the concept and its potential application in other hydropower plants.

The case study regarding erosion classification [5] has shown that a classification of the cavitation intensity is possible based on images, especially with the CNN' approach. An even better result could be achieved with the decision about the presence or absence of cavitation with an accuracy above 97%.

5 References

[1] Enel Green Power, *PresAGHO is a new predictive maintenance model for hydroelectric power plants"*, [Online], 2019

[2] Mallick S., *Head Pose Estimation using OpenCV and Dlib,* [Online], 2016

[3] OpenCV Foundation, *OpenCV – Computer Vision Library* [Online], 2021

[4] Aasnes A. et al, *Predictive maintenance and life cycle estimation for hydro power plants with real time analytics*, Conference Hydro 2018, Gdansk, Poland

[5] Kraxner T., *Grading Erosion on Pelton Wheels from Cavitation with Images*, FH Vorarlberg, Dornbirn, 2022