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## ► To cite this version:

Stephen Catsamas, Canwei Pang, Baiqian Shi, David Mccarthy. Non-contact, low-cost, camera-based turbidity sensing: the future of water quality measurements for IoT. Novatech 2023, Graie, Jul 2023, Lyon, France. hal-04184151

**HAL Id: hal-04184151**

**<https://hal.science/hal-04184151>**

Submitted on 21 Aug 2023

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## Non-contact, low-cost, camera-based turbidity sensing: the future of water quality measurements for IoT

Détection de turbidité sans contact, à faible coût et basée sur une caméra : l'avenir des mesures de la qualité de l'eau pour l'IoT

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### RÉSUMÉ

La demande de données en temps réel dans les systèmes d'eaux pluviales nécessite le développement de capteurs à faible coût pouvant être déployés à grande échelle. Les solutions actuelles à faible coût pour la surveillance de la turbidité utilisent des technologies dans l'eau. Un capteur de turbidité basé sur l'image sans contact et hors de l'eau permettrait de réduire les coûts de déploiement et de maintenance, tout en offrant une fiabilité améliorée. Dans le cadre du développement d'un tel capteur de turbidité hors de l'eau à faible coût, des méthodes algorithmiques fiables d'estimation de la turbidité à partir de données d'image sont nécessaires. Ici, trois de ces méthodes sont proposées et évaluées dans une expérience de laboratoire pour déterminer leur adéquation à l'application des capteurs. Il s'avère qu'une méthode qui repose sur le contraste entre un fond de référence noir et blanc fonctionne avec précision sur une plage de 1 à au-delà de 200 NTU et est également robuste contre la turbulence de la surface de l'eau. De plus, le procédé est peu exigeant en ressources de calcul, ce qui lui permettra d'être facilement mis en œuvre sur un microcontrôleur à faible puissance à utiliser dans une future conception de capteur de turbidité à faible coût.

### ABSTRACT

The call for real time data in storm water systems requires development of low-cost sensors which can be deployed at scale. Current low-cost solutions for turbidity monitoring utilise in-water technologies. A non-contact, out of water image-based turbidity sensor would provide reduced costs in deployment and maintenance, while also offering improved reliability. In the journey to develop such a low-cost out-of-water turbidity sensor, reliable algorithm methods of estimating the turbidity from image data are needed. Here, three such methods are proposed and evaluated in a lab experiment to determine their suitability towards sensor application. It is found that a method which relies on the contrast between a black and white reference background performs accurately across a range of 1 to beyond 200 NTU and is also robust against the turbulence of the water surface. Additionally, the method is undemanding of computational resources which will enable it to be easily implemented on a low power microcontroller to be used in a future low-cost turbidity sensor design.

### KEYWORDS

low-cost, non-contact, real-time, sensing, turbidity

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## 1 INTRODUCTION

Real-time low-cost monitoring of urban stormwater systems has recently come into focus for its ability to provide large datasets on stormwater systems, allowing operators to obtain a complete picture of their water system. Turbidity is a key indicator of quality as it can be correlated with the presence of other substances which indicate the health of the stormwater system. Imaged based turbidity measurement has been of interest due to its potential to as a low-cost measurement technique (Liu et al., 2018).

Currently low-cost turbidity monitoring uses in-water sensors. An out of water turbidity sensor had numerous advantages over the in-water type. Deployment costs are reduced as the sensor does not need to be fixed to the channel bed, this can also increase safety as confined space entry can be minimised. Reliability is also improved as there is no chance of water ingress damaging the sensor from imperfect waterproofing. Submerged turbidity sensors experience degradation in performance over time as bio-growth clouds the optical components. Out of water sensor are immune to this issue and hence would require significantly less maintenance.

As a first step towards a low-cost real-time sensor a measurement principal needs to be developed. For the camera setup used here, an estimator method is needed to take the image data and transform this into a turbidity reading. Existing literature had demonstrated the feasibility of extracting turbidity from image data, however there exist a few common issues which need to be overcome before field deployment. They either require standard lighting conditions (Mullins et al., 2018; Toivanen et al., 2013), require a fixed water surface (Chai et al., 2017; Huang et al., 2021), or are focused on citizen science programs (Leeuw and Boss, 2018). A takeaway from these prior works is that using a reference background can provide high accuracy results. In this abstract, a number of different estimator techniques are evaluated against each other for suitability with lab sample data.

## 2 METHODS

### 2.1 Experiment

To gather the relevant image data on which to test the estimation methods, an experimental setup was developed as per Figure 1. The setup mirrors a potential installation of a camera above a storm water system. A printed sheet of paper serves as a reference background. In a field installation this may be provided by a printed PVC pipe. The OV7675 compact camera module was used for its small size (6 x 6 mm) and ease of integration with low-power microcontroller units. Here, a computer was connected to store the captured images to file. For a range of turbidity levels, images were taken for both still water surface conditions and turbulent water surface conditions (see Figure 2). This was done to see how each method performed in ideal and real-world conditions where the water surface is likely to be turbulent. The turbidity of the water was changed by adding sediment and its value was manually checked using an Orion AQ4500 Turbidimeter.

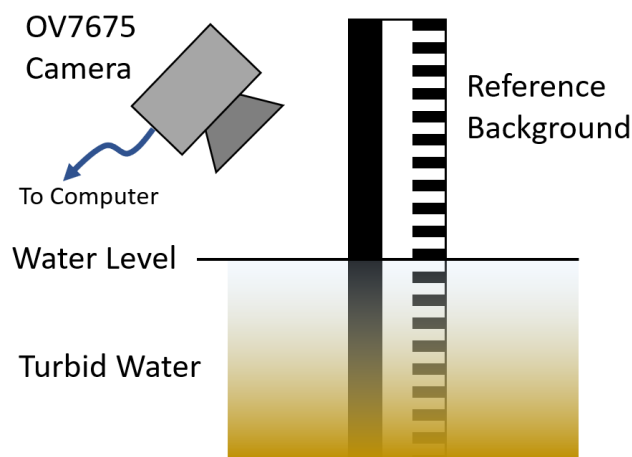


Figure 1: Diagram of experimental setup. Turbid water is held in a glass open-top tank. A paper is placed behind the glass with a black, white and alternating printed pattern to serve as a reference background. The OV7675 camera is held above the water surface looking towards it at a near 45° angle to the horizontal.

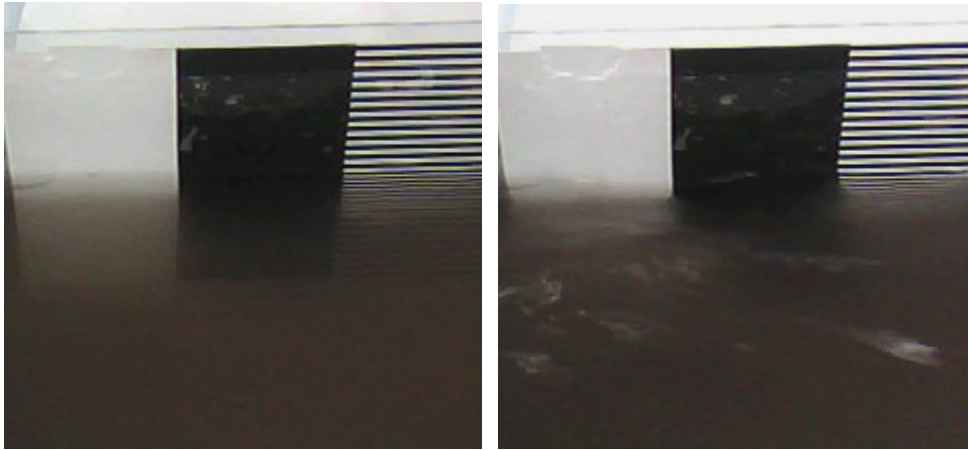


Figure 2: Example image taken from OV7675 during experiment. Left: still water surface. Right: turbulent water surface. The white, black, and alternating regions can be seen in the background.

## 2.2 Algorithms

Three methods were used to interpret the images from the non-contact sensor. These are explained below.

### 2.2.1 Exponential Fit

Due to the Beer-Lambert law, it is expected that the intensity of the light decays exponentially as it passes through the fluid. The rate of attenuation is dependent on the turbidity of the fluid and this method attempts to measure the attenuation rate by fitting an exponential to the image greyscale intensity values on the alternating background. This provides a contrast reference to correct for lighting conditions. A correlation between the attenuation rate and turbidity can then be performed to get an estimate of the turbidity.

### 2.2.2 Contrast Integral

Similar to the exponential fit method, the contrast integral measures turbidity through a proxy variable of the integral of the image intensity values up to the surface of the water. Specifically, the integral of the difference in intensity between the white and black regions is used to reduce the effect of illumination conditions. As this method integrates over a large region of the image data, it should be more robust to noise and reflections.

### 2.2.3 Contrast Ratio

The contrast ratio is the simplest method tested here. The ratio between the average value of the black and white regions is taken. It is expected that with increasing turbidity this ratio will decrease as the two regions both approach the colour of the turbid water. Like the contrast integral, this method takes an average over a large region of the image, and may be less susceptible to errors due to robustness reflections and noise.

## 2.3 Analysis

The methods are marked against five performance metrics. Memory usage: how much computational memory is required for the given algorithm. Processing time: the computational time required relative to the fastest algorithm. For both memory and processing, a lower requirement is better.  $R^2$ : the  $R^2$  value of the linear correlation, a measure of the variation from the linear model. Range: the NTU values over which the algorithm is demonstrated to work. Coefficient of variance: the mean coefficient of variance of the algorithm outputs for a given water turbidity level in both still and turbulent water surface conditions. This demonstrates the repeatability of the algorithm and its robustness against real world conditions.

For each of the algorithms, the relationship between the algorithm output and the manually measured turbidity value (via Orion) is investigated with a linear or linear-log regression. For each regression, the probability of the null hypothesis that the gradient is zero is  $p < 0.05$  which indicates that the fit is appropriate. For the exponential fit method, the curve fit becomes unstable above 50 NTU or in turbulent water surface samples and gives non-sensical results. Therefore, these points therefore have not been used in the exponential fit analysis.

## 3 RESULTS

The comparison between the algorithm output's and the measured turbidity along with the regression line is displayed in Figure 3. Each of the method's outputs is seen to correlate with the turbidity and hence are viable as a turbidity estimation. The methods were compared against the five performance metrics (Table 1). Overall, they suggest that the contrast ratio method performs the best on all metrics. For the exponential fit method, a coefficient of variance could not be computed as the algorithm was not able to process all the data for the turbulent water surface. This was because the fine features of the alternating background could no longer be resolved. In opposition to this, the contrast ratio has the lowest coefficient of variance as the still and turbulent

water surface results performed similarly and it's repeat measurements had the least spread. The range and performance of the proposed methods compares similarly within existing methods (Liu et al., 2018). This shows that the simplicity of the methods do not adversely affect their measurements.

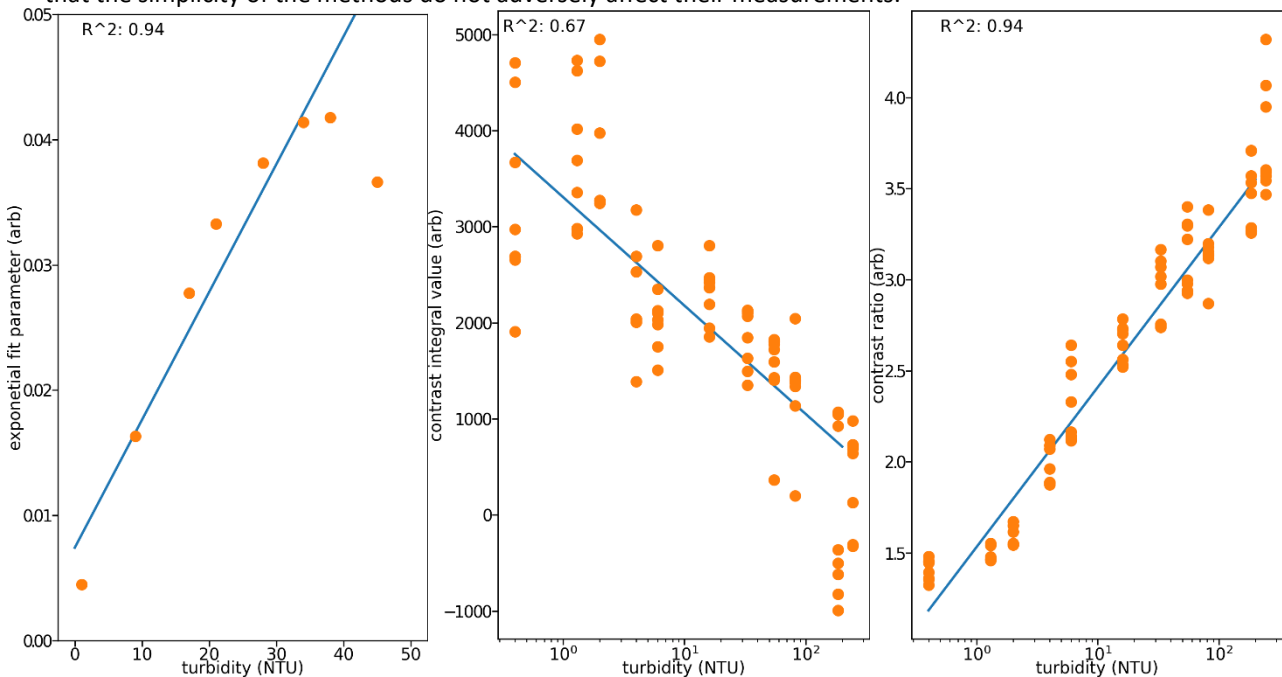


Figure 3: Linear correlation of algorithm outputs against measured turbidity. Left: exponential fit algorithm (lin-lin plot), the last datapoint is excluded from the analysis as it is outside of the apparent linear regime. Centre: contrast integral algorithm (lin-log plot). Right: contrast ratio method (lin-log plot).

Table 1: Summary comparison of turbidity estimation methods. Red dash: unable to be calculated.

|                                  | <i>Exponential Fit</i> | <i>Contrast Integral</i> | <i>Contrast Ratio</i> |
|----------------------------------|------------------------|--------------------------|-----------------------|
| <i>Memory usage</i>              | >640 bytes             | <100 bytes               | <100 bytes            |
| <i>Processing time</i>           | 533%                   | 116%                     | 100%                  |
| $R^2$                            | 0.94                   | 0.67                     | 0.94                  |
| <i>Range (linear or lin-log)</i> | 1 to 30 NTU            | 1 to >200 NTU            | 1 to >200 NTU         |
| <i>Coefficient of Variance</i>   | -                      | 0.68                     | 0.05                  |

#### 4 CONCLUSION

As part of the sensor design for a low-cost out of water turbidity sensor, various algorithms were proposed and tested for estimating the water turbidity from image data. Here it is found that a method based on the contrast ratio provides a simple, robust, and accurate method for out of water turbidity estimation and it can perform well from 1 to beyond 200 NTU. Due to its simplicity, it requires very minimal computational resources for the image processing and may even be performed directly from the image data stream. For future work this algorithm may be further refined and implemented on an OV7675 camera-based system to create a low-cost turbidity sensor for real time urban stormwater monitoring.

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