River Stage Measurement Using Advanced Image Processing Techniques

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***Abstract*— This study explores the application of advanced image processing and deep learning techniques for river stage measurement, a critical component in hydrological monitoring. Traditional methods, while effective, face limitations in terms of cost, labor, and scalability. We employ deep learning models such as SegFormer and convolutional neural networks to segment and analyze river imagery, offering a more cost-effective and scalable alternative. Our methodology utilizes high-resolution imagery to autonomously detect river stages, demonstrating significant potential through alignment with ground truth data. The results highlight the advantages of non-contact measurement methods, particularly in challenging environmental conditions. This paper provides a comprehensive framework that enhances river stage measurement accuracy and efficiency, contributing to sustainable water resource management and environmental monitoring.**

Keywords- river stage, computer vision, hydro informatics, deep learning, segmentation, logan river

I. INTRODUCTION

Monitoring river stages is a fundamental aspect of hydrological studies, environmental management, and flood risk analysis. Accurate and timely river stage data support applications ranging from flood forecasting and infrastructure planning to ecological habitat assessment [1]. Traditionally, river stage measurements have relied on in-situ gauges or radar-based systems, which, although effective, are often limited by cost, intensive maintenance, and restricted spatial coverage [8].

Recent advances in computer vision and machine learning have begun to address these challenges, offering scalable and non-contact alternatives for river monitoring [9]. By analyzing high-resolution imagery, automated methods can detect and quantify water bodies without requiring extensive manual labor or extensive sensor networks. Deep learning architectures, particularly semantic segmentation models, have shown promise in distinguishing water from surrounding terrain in diverse and complex visual scenes. As these technologies mature, they hold the potential to reduce field visits, lower operational costs, and increase measurement frequency. Ultimately, such approaches could lead to more informed decisions in water resource management and more proactive responses to hydrological hazards.

Despite these technological strides, several challenges remain. Environmental variability, such as changes in illumination, seasonal vegetation dynamics, and reflections on the water surface, can reduce the accuracy of image-based analyses. Furthermore, logistical constraints at remote field sites, including limited access to power and internet, can complicate data collection and processing.

This study aims to enhance the accuracy and efficiency of image-based river stage measurement through advanced semantic segmentation techniques. Specifically, we employ the SegFormer architecture, a transformer-based model known for robust performance in a variety of segmentation tasks. By leveraging this state-of-the-art approach, we develop a framework to segment high-resolution images of river scenes and derive river stage estimates through pixel-based analysis and regression modeling. Through this research, we seek to contribute a more reliable and scalable method for hydrological monitoring, ultimately supporting improved water resource management and environmental decision-making.

The contributions made by this paper are listed below-

- Integration of Advanced Semantic Segmentation: Effective leverage of the SegFormer architecture for precise river boundary delineation.
- Non-Contact River Stage Measurement Framework: Introduction of an image-based, scalable, and cost-effective method correlating water pixels to stage height.
- Empirical Validation on Real-World Sites: Demonstration of robust performance and alignment with ground truth data across multiple river environments.

The remainder of this paper is structured as follows: In Section II, we review related work on image-based river measurement and semantic segmentation in hydrology. Section III details data acquisition, annotation, our proposed methodology and model architecture. Section IV presents our experimental setup and results. Section V discusses about this research potentiality and potential future work and Section VI discusses conclusion of the paper.

II. RELATED WORK

Accurate and timely measurement of river stage (water level) is crucial for various hydrological applications, including flood monitoring, water resource management, and environmental studies [1, 4, 14]. Traditional methods for measuring river stages, such as in-situ gauges or radar-based systems, can be expensive, labor-intensive, and limited in spatial coverage [7, 8]. With the advent of image processing techniques and deep learning, there has been a growing interest in developing cost-effective and scalable approaches for river stage measurement using image data [2, 6, 9, 19, 20].

Recent advancements in computer vision and semantic segmentation, particularly with the introduction of deep learning methods, have opened new opportunities for extracting valuable information from images and videos [2, 3, 6, 9, 29]. These techniques have shown promising results in accurately detecting and delineating water bodies, enabling precise measurements of river stage and width [5, 13, 15, 21, 30]. Various deep learning architectures, such as convolutional neural networks (CNNs), fully convolutional networks (FCNs), and transformer-based models, have been employed for this task, achieving state-of-the-art performance [2, 16, 17, 18, 23, 26].

The primary objective of this study is to explore and evaluate advanced image processing techniques, specifically deep learning-based semantic segmentation methods, for accurate river stage measurement. By leveraging the power of these techniques, we aim to develop a robust and efficient framework that can automatically detect and segment water bodies from images or videos, enabling precise river stage estimation.

Several key challenges need to be addressed in this context, including handling varying environmental conditions, dealing with occlusions and reflections, and ensuring accurate segmentation of water boundaries [9, 22, 24, 28]. Additionally, the proposed framework should be scalable and adaptable to different river systems and data sources, such as fixed cameras, unmanned aerial vehicles (UAVs), or satellite imagery [11, 12, 19, 25, 27].

This paper presents a comprehensive review of existing techniques and methodologies for river stage measurement using advanced image processing techniques. We provide a detailed analysis of state-of-the-art deep learning architectures and their application in this domain, highlighting their strengths and limitations. Furthermore, we propose a novel framework that integrates cutting-edge semantic segmentation models with post-processing techniques to enhance the accuracy and robustness of river stage measurements.

Deep learning has also emerged as a key technology for image segmentation in hydrological contexts. Research introduced SegFormer, a deep learning architecture designed for semantic segmentation tasks, which has shown promising results in image processing and computer vision applications [2]. The model's ability to segment complex images with high accuracy makes it suitable for detecting river boundaries. Similarly, another research article showed a benchmark for semantic segmentation of waterbody images, providing a framework for training and testing deep learning models on a diverse dataset [3]. This study contributes to the understanding of image segmentation in water-related contexts.

Machine learning is playing an increasingly significant role in hydrological monitoring. A research article explored the use of computer vision to monitor river flow during flood events, highlighting the advantages of non-contact measurement methods [4]. Their work underscored the importance of machine learning in processing large volumes of image data and deriving meaningful insights for hydrological applications. This approach aligns with the project's aim to leverage scalable computing resources for automated river width measurement.

The proposed approach is evaluated on multiple datasets, including publicly available benchmark datasets [3, 10] and real-world data collected from various river systems [11, 12]. Experimental results and quantitative comparisons with existing methods are presented, demonstrating the effectiveness and practical applicability of the proposed framework.

This study contributes to the field of hydrological monitoring and water resource management by providing a comprehensive and scalable solution for accurate river stage measurement using advanced image processing techniques. The findings and insights gained from this research have the potential to facilitate more efficient and cost-effective monitoring of river systems, ultimately supporting decision-making processes and contributing to sustainable water resource management practices.

III. METHODOLOGY

In this section, we detail the proposed methodology for image-based river stage measurement, outlining each component of our workflow. Starting from high-resolution imagery acquisition, we discuss the data preprocessing steps and annotation procedures that prepare our dataset for segmentation. We then introduce our chosen deep learning architecture – SegFormer for semantic segmentation of river scenes and describe how we adapt and fine-tune this model for our specific application. Finally, we present the pixel-based analysis and regression approach used to translate segmented images into meaningful stage measurements. Together, these steps form a streamlined, automated pipeline designed to deliver accurate, non-contact river stage estimates suitable for a variety of hydrological monitoring scenarios.

A. *Data Acquisition*

Efficient data acquisition and management are critical components of our river monitoring system. The field site used for this project were the Logan River by the West Bridge behind the Utah Water Research Laboratory (UWRL) in Logan, Utah and Darwin Bridge near Blacksmith Fork in Nibley, Utah. The Logan River was chosen due to significant seasonal changes in flow and stage, while the UWRL site was chosen due to its easy access to AC power and Wi-Fi and the BF site was chosen due to the channel variability though this site has no AC power and internet.

Data was collected from the sites using a custom Python script developed for a Raspberry Pi 3B+ (Raspberry Pi Foundation, Cambridge, England), which controls a Vivotek IB9387-HT-A high-resolution camera (Vivotek, New Taipei City, Taiwan) (shown in Figure 1). The script triggers the camera at 30-minute intervals to capture still images and 10-second videos. This robust automation ensures consistent data collection and streamlines storage.

Both still images and videos are captured at a resolution of 2560 x 1920, with images averaging around 2 megabytes in size and videos around 80 megabytes. Given the high-quality data and frequent capture rate, the post-capture steps include compression, decoding and optimization, which help maintain efficient data collection.

(a) (b)

Figure 1: Data collection module and camera for **(a)** Waterlab Site and **(b)** Blacksmith Fork Site.

B. *Data Annotation*

Annotation plays a crucial role in river monitoring systems because it provides a structured approach to training computer vision models, allowing them to understand and distinguish different features within images. To develop this river monitoring system, the Computer Vision Annotation Tool (CVAT) (https://www.cvat.ai/) was utilized to annotate a diverse dataset of images from the field site. Each image was labelled with two key classes - 'water' and 'vegetation' (Figure 2). This established a binary classification fundamental for training the segmentation model to identify and separate water bodies from surrounding vegetation accurately.

Figure 2: Annotated Image of Water Lab Site where blue section represents vegetation and pink portion represents waterbody.

C. *Model Development*

Research indicated that previous works using the SegFormer model architecture (Figure 3) for semantic segmentation achieved better results than other models in similar tasks.; this finding was a significant factor in choosing SegFormer for our river monitoring system. SegFormer combines Transformer-based architecture with lightweight MLP (Multi-Layer Perceptron) decoders, providing simplicity, efficiency, and robust performance [2]. Given its proven track record in achieving superior segmentation results, it was the ideal choice for our specific needs in aquatic environment analysis; the SegFormer model's ability to deliver high accuracy and efficiency in segmenting complex images makes it instrumental in identifying and analyzing water bodies in our river monitoring system.

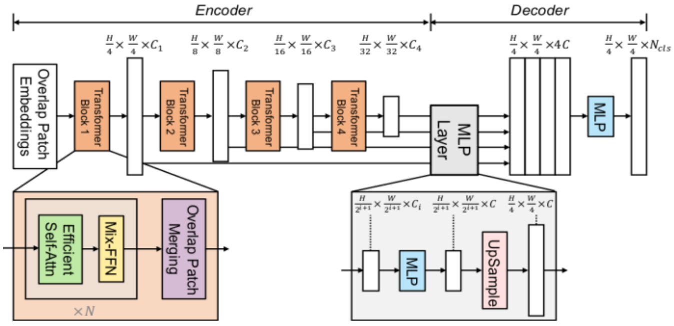

Figure 3: Segformer Model Architecture.

Our approach involved leveraging a pre-trained SegFormer model, specifically 'Nvidia/segformer-b5-finetuned-ade-640-640' [2], designed for use with the ADE-20k dataset [10], which contains 150 classes. Since we were primarily interested in segmenting water, we modified the detection part of the model to focus exclusively on the 'water' class (shown in Table I), ignoring the other classes. This customization allowed the model to overlay a mask on the images, highlighting water bodies within the recorded scenes. This approach helps the model to recognize relevant features and patterns crucial for accurately segmenting water bodies.

TABLE I. ADE20K DATASET IMAGES RELATED TO WATERBODY

ADE20k Dataset	
Labels	***# images***
Water	709
Sea	651
River	320
Waterfall	80

D. *Stage Measurement*

To estimate water levels and predict stages, multiple regions of interest (ROIs) were defined within a set of segmented images on both banks. These ROIs were selected to encompass vegetation and water bodies, ensuring a comprehensive representation of the riverbank's varying conditions. The selection criteria for these regions were based on their potential to capture changes in streamflow, and the spatial extent of the riverbanks determined their size. This approach operates on the premise that as streamflow increases, the spatial extent of water also increases, resulting in a higher pixel count within these designated regions.

After defining the ROIs, the water pixels were counted within each area. This process involved segmenting the images and isolating pixels classified as 'water.' We then calculated the total number of water pixels within each ROI to gauge the spatial extent of the water bodies. The equation for this is:

$$Water\ Pixel\ Count = \sum_{i=1}^{n} I(i) \qquad (1)$$

Where $I(i)$ represents the value of the i^{th} pixel in the ROI, which is 1 for water and 0 for non-water pixels, and n is the total number of pixels in the ROI.

Following this, a time series dataset was created to analyze trends over time, compiling the water pixel counts for each ROI and Logan River Observatory (LRO) water stage data [11, 12]. This data enabled us to explore trends and fluctuations in water levels, which correspond to changing streamflow conditions. Time series analysis helped us identify patterns and correlations, providing insights into the behavior of the riverbanks.

Once the pixel counts were established, a regression model was developed to find a relationship between these counts and the corresponding recorded gage height from the LRO depth sensor at our monitoring site; this step was crucial in identifying a correlation between pixel count and water level. The resulting regression model provided a formula for predicting water levels based on the pixel counts from our ROIs. The predicted values were then compared with the recorded stage to evaluate the model's precision and accuracy. This comparison helped determine whether our regression-based approach could effectively predict water levels, providing valuable insights for further refinement and potential deployment in river monitoring systems.

IV. EXPERIMENTS

In this section, we present the experimental setup and evaluation process used to assess the performance of our proposed method. We begin by describing the datasets employed, including the procedures for image collection and the corresponding ground truth measurements. Next, we detail the model configurations and model hyperparameters. Finally, we report the results of our experiments and compare our findings to existing state-of-the-art approaches, illustrating the practical advantages and potential scalability of our framework.

In addition, all code and scripts used to conduct our experiments and analyses are made publicly available for reproducibility purposes.[1]

A. Model Configuration and Hyperparameters

Our experiments utilized a SegFormer model pre-trained on the ADE20K dataset (specifically, the 'Nvidia/segformer-b5-finetuned-ade-640-640' variant) and adapted it to focus exclusively on the 'water' class. Input images were resized to 640 × 640 pixels, consistent with the model's pre-training settings. Data augmentation (random horizontal flips, minor brightness/contrast adjustments, slight rotations) was applied to improve robustness against environmental variability.

Training was performed using the Adam optimizer with an initial learning rate of 5e-5 and a weight decay of 1e-4. We employed a batch size of 4 images, determined by GPU memory constraints. The learning rate was reduced by a factor of 0.1 at predefined epochs if validation performance plateaued. We trained for up to 80 epochs, implementing early stopping based on validation metrics (Intersection over Union for the 'water' class and validation loss) to prevent overfitting.

B. RESULTS

For the WaterLab site, the original image shows a tranquil river with surrounding vegetation. After segmentation, the water body is clearly defined in blue, with regions of interest (ROIs) marked in red rectangles (Figure 4). Quantitatively, the pixel counts within these ROIs over time show a trend that

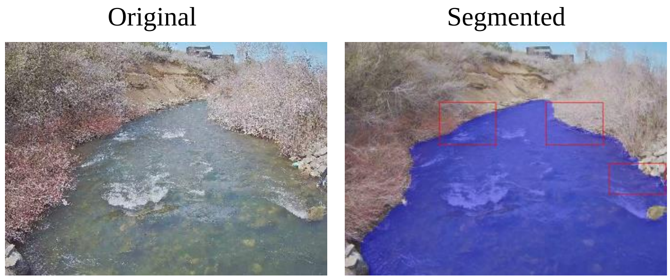

Figure 4: Comparison of original and segmented images at the WaterLab site, highlighting the precision of image segmentation in water detection.

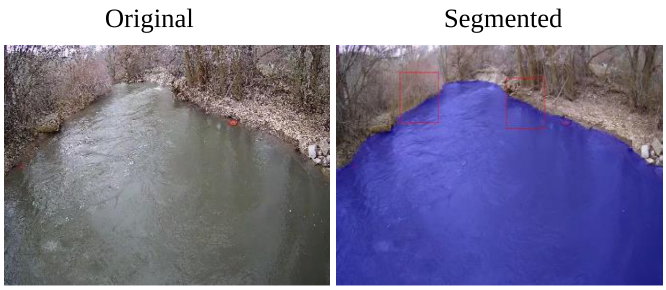

Figure 5: Comparison of original and segmented images at the Blacksmith Fork site, highlighting the precision of image segmentation in water detection.

corresponds with the ground truth data for water stage. Specifically, in the graph presenting the smoothed left bank versus ground truth, the pixel counts correlate with the fluctuations in the actual water stage, revealing the system's sensitivity to changes in water level (Figure 6). The pixel counts fluctuate between approximately 65,000 to 80,000, with water stage values ranging from 60 to 75 cm.

At the Blacksmith Fork site, the segmentation is similarly effective, with the water body isolated from the banks (Figure 5). The graph displaying the smoothed right bank against ground truth from this site shows greater variability, with pixel counts ranging broadly from around 90,000 to upwards of 110,000, and the water stage varying from 60 to just over 70 cm (Figure 7). This indicates a more dynamic environment, with significant changes in water stage reflected by a wider range of pixel counts.

[1] The source code is available at: https://github.com/Razin1996/CS6640_Final_Project

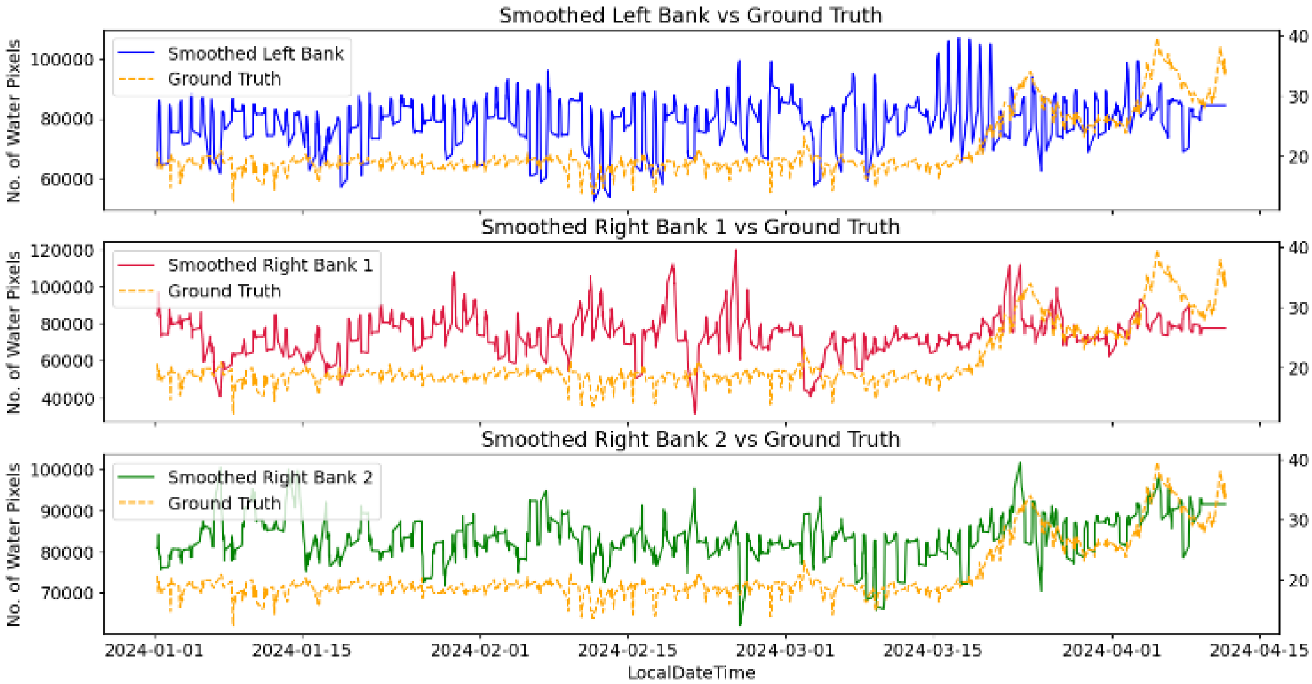

Figure 6: Time-series analysis graph from WaterLab site, displaying the correlation between the number of water pixels detected and recorded water stage measurements.

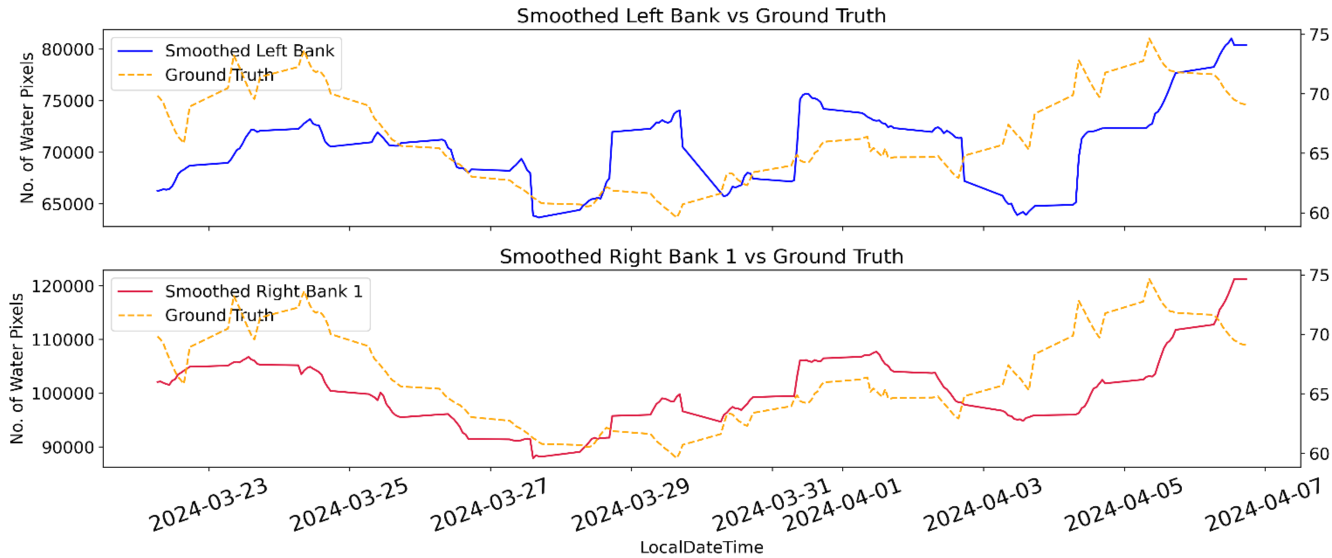

Figure 7: Time-series analysis graph from Blacksmith Fork site, displaying the correlation between the number of water pixels detected and recorded water stage measurements.

V. DISCUSSION

The deployment of computer vision techniques for river stage monitoring has yielded promising results, with segmentation accuracy being a particular highlight. The high-resolution imagery analysis demonstrated the potential for real-time and automated river monitoring, suggesting an alternative to labor-intensive manual measurements. Such advancements could significantly contribute to the timely and cost-effective management of water resources and emergency response during flood events.

However, the study faced challenges, predominantly environmental factors impacting image quality and, consequently, the accuracy of segmentation. Seasonal changes and variable weather conditions, such as fluctuations in light levels, could potentially introduce inconsistencies in data acquisition. These factors necessitate the development of adaptive algorithms capable of maintaining high accuracy under diverse conditions.

Moreover, the significant volume of data generated by high-frequency image capture presented logistical hurdles related to storage and processing. Efficient management of these large datasets is essential to maintain the sustainability of the monitoring system.

The absence of AC power and internet connectivity at some field sites, like Blacksmith Fork, also posed limitations, indicating a need for innovative solutions to ensure continuous operation.

Future work will aim to address these challenges by improving the robustness of segmentation algorithms against environmental variabilities and developing more efficient data management systems. Efforts to optimize power consumption and data transmission for remote locations will also be a focus, potentially incorporating renewable energy sources and advanced communication technologies. Expanding the system's application to a wider array of environments will further establish its utility across diverse hydrological contexts.

VI. Conclusion

The integration of computer vision and machine learning has proven effective for river stage measurement, addressing the limitations of traditional methods. Using advanced semantic segmentation models, our study achieved high accuracy in detecting and delineating river boundaries from high-resolution images. The models demonstrated robust performance across various datasets, confirming their applicability in real-world scenarios. Challenges such as environmental variability and data management were identified, with future work aimed at refining these models to enhance adaptability and efficiency. Overall, this research advances the capabilities of hydrological monitoring systems, offering scalable solutions that support informed decision-making and sustainable management practices in water resource sectors.

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