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Image Processing Techniques Applicable to Wastewater Quality Detection: Towards a Hygienic Environment

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Abstract

This paper presents the latest techniques developed in image processing that can be applied for wastewater quality detection and monitoring. The available techniques are analyzed under their characterization, advancements and benefits in the assessment of the levels of wastewater contamination and identifying the contaminants. It also outlines the primary global wastewater quality parameters that need to be controlled and monitored for any wastewater produced as a result of human activities.

1. Introduction

The increase in world population has resulted in volume escalation of both our domestic and industrial waste materials.These materials can either be organic toxins or inorganic toxins that directly or indirectly find their way into global waters, hence, pose a serious threat to the continued existence of our entire eco-system. In an effort to address this issue effectively, certain regulatory agencies outlined several wastewater quality parameters that should be maintained at certain levels by any wastewater processing plant. The increase in the volume of samples to be assessed due to expanding human activities, coupled with the tedious and meticulous processes involved has outweighed the conventional laboratory-based monitoring techniques by automated systems. Therefore, to satisfy the requirements outlined by the regulatory bodies, more reliable, simple and autonomous real-time techniques have been invented. Wastewater normally emanatesfrom either single or combination of domestic and industrial sources. The contaminants can also come from both urban and rural storm water, which washes fertilizer/pesticides remnants and toxic chemicals [1].

The increased rate of waterborne diseases in the recent past is quite alarming. It was reported by world health organization (WHO) that over 80% of health-related diseases bedeviling developing nations are related to poor water quality, which results in about 30% mortality [2]. To mitigate this problem, WHO and other world regulatory agencies set up some globally acceptable indicators, which serve as the minimum quality standard of any wastewater before been discharged to the waterways [3,4]. These indicators were broadly classified into

organic and inorganic contaminants. The organic contaminants are considered to be more harmful. The quantity of the organic contaminants is measured by the amount of oxygen used to oxidized the wastewater [4].
The predominant and widely practiced method of detecting water quality is through the conventional laboratory mains, which is time-consuming and requires a skilled staff to conduct the test using the appropriate chemical reagents [5, 6]. The tedious nature of work (frequent sample collection) and the complexity and time constraint associated with the conventional laboratory methods of assessing the quality of wastewater, coupled with the need to comply with the international legal laws of securing the environment from toxic contaminants discharged from the sewage and industrial plants, demand more accurate, sensitive and reliable analytical techniques with increased sample throughput. This situation paves the way to the invention of various autonomous in-situ monitoring techniques [7].
Introduction of digital image processing eases the ways of these procedures and produce better results in monitoring the characteristics of wastewater parameters. It also leads to future predictions. In this study, we presents the applications of image processing techniques for wastewater quality detection and explore these techniques to demonstrate the benefits and advancement of wastewater management systems. Image analysis and characteristics of wastewater have been used to monitor and control wastewater treatment plants for the last many years. The process can be divided into three main categories i.e. computer-based imaging system,satellite images and embedded system. The image characteristics are determined using image processing techniques, statistics, fractal dimension and correlation between image analyses with standard measurement [8].

2. Information analysis

Most wastewater quality indicators are not visible and can only be detected laboratory using reagents or high definition microscopic device [4]. Activated sludge process makes it possible to see them with the naked eyes in form of microbial aggregates [9]. To obtain an image to be used for quality detection, there must be images of wastewater indicators, which can be captured through precise and accurate image capturing devices i.e. visible wastewater quality indicators.

2.1 Wastewater Quality Detection

The quality of wastewater is assessed by looking at both its chemical and physical compositions, as well as its micro-bacterial constituents. It requires the services of an artisan trained personnel to perform the assessment using the appropriate standardized instruments [10].
The predominant and widely practiced method of detecting water quality is through the conventional laboratory mains, which is believed to be time-consuming and requires a skilled staff to conduct the tests using appropriate chemical reagents [5]. To properly secure our eco-system, there is the need for regular monitoring and assessment of all water sources and reservoirs especially those that receive their contents from industries, sewage plants, cultivated lands and even running water from urban areas. To achieve this, we require the frequent collection of water samples at specific time intervals and positions. Preferably, samples should be collected at the main water inlet, midway and the final chamber, to closely keep track on the variation of the level of water quality [10].
Water contamination can also be regarded as environmental pollution because it has a direct effect on both plants and other living organisms in the vicinity. The rate at which the climate is changing due to environmental degradation caused by human activities and poor management is quite alarming, thus, researchers and environmental conservation agencies have intensified their activities (i.e. research, environmental policies and human enlightenment) in recent years. In some countries, statutory laws have been established that compel any city that has reached a certainnumber of inhabitants to provide a well-equipped wastewater treatment plant, which will not only treat their sewage waste but also monitor other water parameters that could be harmful to the eco-system [10].

2.2.1Wastewater Quality Indicators

The globally acceptable indicators used to measure wastewater quality as outlined by World Health Organization and relevant health agencies are broadly classified into organic and non-organic substances. The organic substances are the most hazardous parameters and are not easily eliminated using filtration, their presence is normally detected by the quantity of oxygen required to oxidize the substance. The global standard parameters to consider are the amount of Biological Oxygen Demand (BOD), Total Organic Carbon (TOC), Chemical Oxygen Demand (COD), the percentage of Nitrogen and Phosphorus, active sludge mixed liquor suspended solids (MLSS), Total Suspended Solids (TSS) and the Sludge Volume Index (SVI) in the treated water [4]. Moreover, there are other micro-substances such as clofibric acid, carbamazepine, primidone or iodinated that are considered to be pharmaceutically and hormonally reactive pollutants [11]. It is also important to define the accepted levels of these quality parameters, not only to primary effluents but for secondary effluents as well, before the treatment methods are formulated. Thus, even in the case of introducing image processing techniques for wastewater quality management, it is essential to pre-determine the threshold quality parameters, thus, the algorithms could be optimized to make fast outputs. In the case of some toxic contaminations, time-optimization in the monitoring process plays a critical role in taking immediate steps to minimize the risks and hazards.

2.1.2 Automated Wastewater Quality Monitoring Systems

Since the inception of automated monitoring techniques, there has been a significant reduction in reported cases of both water and environmental contamination caused by the discharge of poor quality wastewater [12]. Unlike the conventional methods that involve frequent sample collection, this technique uses flow analysis procedures to analyze the massive number of samples within a short time. It also allows reproducibility and consumes fewer amounts of chemical reagents [13].

2.1.3 Analytical Flow Injection Techniques

The concept of automatic flow analysis started way back in 1950's when the demand for a clinical test for diagnostic purposes has overstretched the then technology and workforce, making it unprofitable to manage. These challenges lead to the development of Segmented Flow Analysis (SFA) [14]. This technique is fast and capable of processing a large number of samples with fewer reagents. SFA serves as the backbone of modern flow techniques.

Since the inception of automatic analytic diagnostic techniques, quite a number of methods has been developed with the capability of performing both in-situ and real-time monitoring of wastewater parameters. Some of them are Flow Injection Analysis (FIA), Sequential Injection Analysis (SIA), Multi-Commutated Flow Analysis (MCFIA), Multi-Syringe Flow Analysis (MSFIA), Lab-On-Valve (LOV) and Multi-Pump Flow Systems (MPFS) [15-17]. Some setups incorporate two or more of the techniques for a better result where each can assess multiple parameters when it is used as a tool in an automatic analyzer.

Prior to the abundance and affordability of computers, FIA dominated among the above methods, similar to SFA it does not require computer facility, unlike the other techniques that require computational machines and compatible software to function. However, at present, with the high affordability of many users for efficient computers and compatible software, SIA and other subsequent techniques have outdone FIA and SFA. With modern computing facilities, they have very high processing speed, a significant level of flexibility, ability to perform multiple parameter analysis with high precision, accuracy and less human interference. Thus, analytic flow technique can be categorized into two generations, one which requires more human interference and does not involve computers (SFA and FIA) and the subsequent techniques (SIA, MCFIA, MSFIA, LOV) that involves less human involvement in processing and decision making [14-17]. Nevertheless, they all have common peripherals such as the impulse pump that serves as liquid injector and several plastic connectors or manifolds for conveying liquids to detectors.

3. Image Processing Techniques for Wastewater

3.1 Introduction to Image processing phases

There are four phases of image processing techniques, namely the image acquisition, pre-processing (noise removal and image enhancement), image segmentation, and image analysis [18]. Each of the mentioned phases has enhanced techniques to ensure high-quality image. A typicalimage processing block diagram is shown in Figure 1 and Figure 2 outlines in detail the stages of image processing and analysis.

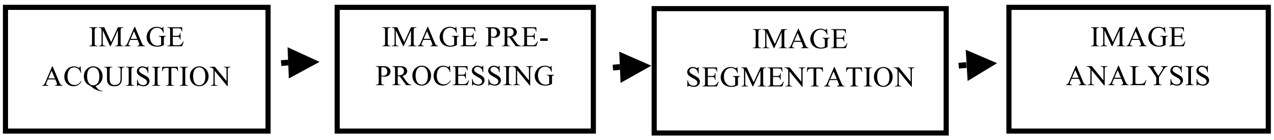

Figure 1: Image processing and analysis

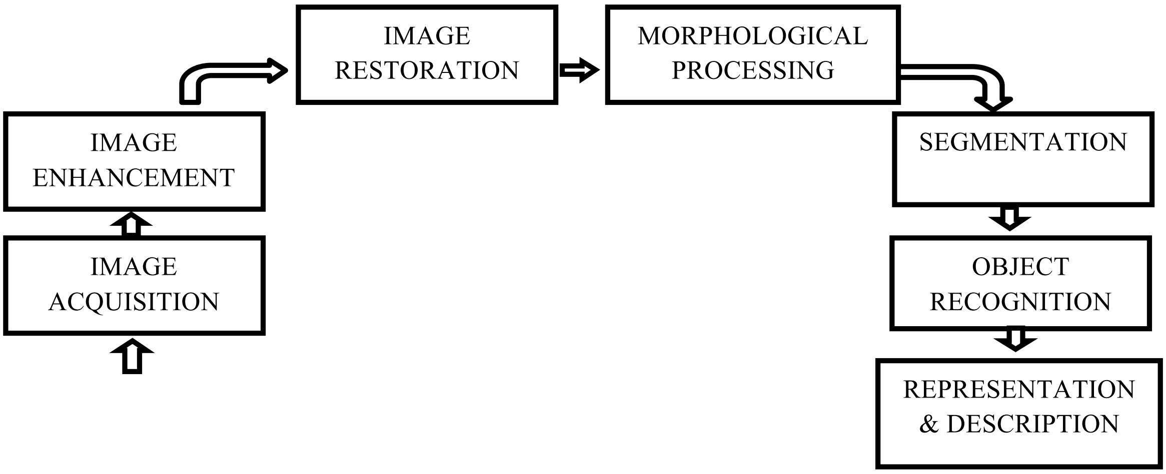

Figure 2: Detailed Image processing and analysis block

3.2 Image Acquisition

This phase is very critical and considered as the cornerstone of the proper image processing system. The acquisition consists of three steps; the region of interest object reflection, an optical system to focus the energy, and sensors to detect the amount of energy. The acquired image is then stored in a magnetic or an optical storage device using a specialized software programme. Various image acquisition techniques are reported in the literature [18]. Depending on the available microscopy technique to use, the slides are prepared and assembled accordingly. The microscope is usually connected to an imaging system that has a charge-coupled device (CCD) camera for image and video capturing of the sample instantly for onward processing on a computer system. Grijspeerdt and Verstraete [19] employed dark field microscopy to assess sludge settling ability and concentration using a specially designed Microsoft visual C++ software to perform the imageanalysis. Dark-field microscopy has a simple setup and provides sufficient contrast to enable viewing and capturing of unstained cells. The drawback with this method is it high illumination rays when beamed on the cell tissues is capable of damaging the samples.

A predominantly and commonly used technique is bright field microscopy. Its simple preparation and setup mechanism has been the main reason behind its popularity and wide acceptability [20]. Similar to the previous, it can be usedfor both live viewing and image capturing of cells. In situations where the sample cells have very low contrast, the pigment has to be stained to increase resolution. The staining sometimes destroys or introduces some anomalies to the samples, which serves as the main drawbacks of this technique [20]. Figure 3 shows a special microscope from Dialux 20 optic microscope produced by Leitz, Wetzlar [21].

A superior technique to bright field microscopy is the phase contrast. It is capable of capturing details that are invisible to the bright field. It is recommended for use on transparent, unstained specimens. Its drawback is that thick samples, halo effects or phase artefacts often result in image distortion around sample perimeter. Mesquita*et al.*, [22] employ both epifluorescence and bright field microscopy to analyze and classify four abnormal conditions in wastewater process. Fluorescence microscopy uses fluorescent molecules to stain the cells or tissues samples. It can be used to trace the location and pattern of the cell samples. The problem with this method is since fluorescence is not permanent (fades with light); photo-bleaching tends to occur, as the specimen is viewed [23].

Another promising image acquisition technique is Nomarski microscopy also called differential interference optics. Like phase contrast microscopy, it supplies contrast to both transparent and unstained live cells. It is capable of producing quasi-3D images. It is not suitable for thick samples which serve as it limitation [24].
Also worth mentioning is Confocal microscopy, popularly known as confocal laser scanning microscopy (CLSM). Is an optical imaging technique that uses a spatial pinhole to focus an optical light on the image formation. Unlike the conventional microscope that illuminates and penetrate the entire specimen without control, CLSM is capable of focusing the light beam at a specific point and step-depth penetration. This property tends to increase the sampled image resolution and contrast. The drawback with this technique in addition to high cost is the wavelength of the rays produced by laser light, which limits the device operational range [25].
Electron tomography (ET) is another image acquisition technique it is an extension of transmission electron microscope (TEM). It incorporates TEM methodology to capture the 3D image details of intra-cellular and macro-molecular samples. The technique involves passing an incremental beam of electrons through the sample in a rotary form with reference to the target sample [26].

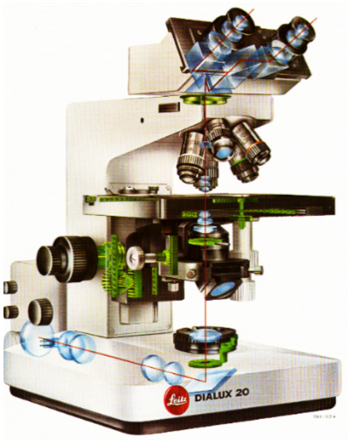

Figure 3: Microscope from Ernst Leitz Wetzlar Microscopes [21].

3.3Image Pre-processing
The next stage after sample acquisition is preprocessing, it is a stage that ensures sample collected is clean and free from unwanted distortions as well as enhances the sample important parameters for onward processing. Improving the image visual appearance can be achieved by adjusting it pixel brightness; this concept is known as Image Enhancement. It comprises of techniques that transform image to a better form that is easily interpreted by both human and machine. Image enhancement does not actually increase the image inherent details rather it emphasizes and improve the image specific properties or attributes. A number of enhancement algorithms exist but they are greatly influenced by the image modality and nature of the application [27, 34]. An image deformation can be eliminated/mitigated by using definite or statistical mathematical models [28]. The common and widely applicable technique that serves as the bases of other enhancement techniques is contrast stretching, histogram equalization (HE), histogrammodified local enhancement (HMLCE), fuzzy contrast enhancement, log transformations and thresholding transformation [29-33].

3.3.1Linear Contrast Stretching technique
Contrast stretching is a technique used to increase an image brightness level to the required satisfaction of the image analyst. Poor image contrast could be due to the inadequate illumination level in the sampling surrounding or due to improper sensitivity in the image-capturing device. Hence, a means of adjusting the image contrast is needed to compensate and restore it level to the required quality. The concept of contrast stretching is based on stretching the image pixels dynamic range. Linear contrast stretching is considered the simplest form of enhancement algorithms, which extends an image over it entire grey-level spectrum. [19, 29]Figure 4a shows an original floc image with it un-stretched/confined histogram. While 4b is the image after stretching which has better contrast than the original and as can be seen from it histogram. The pixels dynamics has been stretch over the spectrum towards the right 255 value away from the deep grey value. It is suitable for in-situ or deep-water applications where the illumination and contrast level are poor [29].

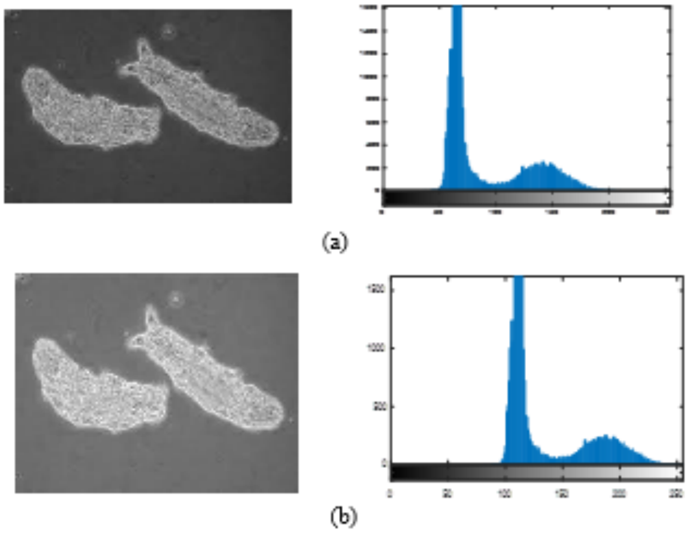

Figure 4: Contrast stretching enhancement technique
(a) Original floc Image (b) Floc image after contrast stretching

3.3.2 Histogram equalization technique

Histogram equalization (HE) technique is one of the commonly used enhancement techniques for adjusting an image contrast level. An image that has less illumination level tends to have a histogram that skewed towards the lower side of the grey scale as can be seen from (Figure 5a) below. The darkness makes the histogram to concentrates towards the lower left side. To increase the image brightness, the histograms need to be stretch out from the grey level to have a uniform distribution across the spectrum. Figure 5b shows the new image and its histogram after applying HE technique. The histograms are evenly spaced and broadly distributed across the spectrum, which is why itconsiders global technique [30].

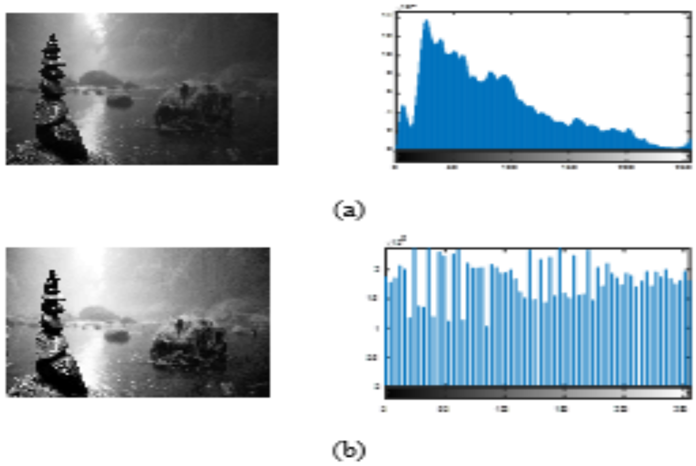

Figure 5: Histogram equalization enhancement technique
(a) Original floc Image (b) Floc image after contrast stretching

3.3.3 Histogram modified Local Contrast enhancement (HMLCE)

The major drawback of previously mentioned enhancement technique (i.e HE) is the loss of local information in the sample due to over enhancement that is caused by using cumulated histogram as the mapping function. To mitigate this problem, the input histogram is modified so that it looks uniformly distributed. Therefore, HMLCE technique employs two-stage processing namely histogram adjustment and local contrast enhancement. The primary goal of this technique is to generate a uniformly modified histogram that differs slightly from the main input histogram. In this case, the number of pixels in the sampled region has little interference on the processing of the global transformation [31]. Sundaram et al., applies HMLCE to a mammogram images which gives better resultant image with improved local details than ordinary HE. They uses histogram modification as an optimization method along with the LCE technique. Three indices were used as the performance measurements namely enhancement measurement (EME), absolute mean brightness error (AMBE) and discrete entropy (H) [32].

Rule-based system

3.3.4 Fuzzy contrast enhancement technique

The fuzzy logic capability of exhibiting unique property similar to human perception makes it suitable for image processing and other so many applications. It can provide a solution to problems that have no clear solution so long the solution can be presented/represented using linguistic terminologies. It basically has three main steps that involve; Fuzzification, Inference engine and De-fuzzification. Fuzzification in the context of image enhancement involves the assignment of membership function in order to map the image pixels to the fuzzy plane. Assume an image with ‘nxm’ size, with pixel range of 0 to 255 will be scale/mapped to between 0-1 ranges on the fuzzy plane. The inference stage involves the usage of the rule-based expert system to transform/modify the image pixels to achieve the desired enhancement. The defuzzificationinvolves transforming back the image from fuzzy plane to its original pixel plane using inverse transform [33].Hanmandlu et al., [34] suggested a fuzzy logic enhancement techniques where Gaussian membership function was used to fuzzifies an underexposed colored image. The fuzzified image was enhanced with the aid of general intensification operator [35]. A new fuzzy automatic contrast enhancement (FACE) technique was proposed in [35]. The method first segment the image through fuzzy clustering where pixels having similar colors and characteristics are grouped into small clusters. This automated technique enhances image quality by eliminating visual artifacts and excessive image straining. This is achieved without any human-defined parameter [36].

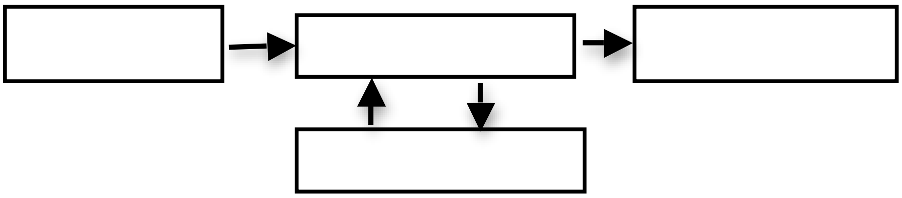

Figure 6: Fuzzy logic process diagram

3.3.5 Log transformation

Log transformation is another enhancement technique that projects a fractional low-level input image pixels grey value to a broader output range values. It inverse log transformation does exactly its opposites. This process is specifically useful in situations where the input grey level has a large range of values or when the processed image dynamic range has exceeded the device display capability such that only the brightest pixels are projected on the display screen. An appropriate way to address this kind of problem is to use log transformation. Its expression is given in equation (1.0) below;

$$S = C \log(R + 1) \qquad (1.0)$$

where S and R represent the image output and input pixels respectively. The input pixel R is assumed to be ≥ 0. Since R takes zero value inclusive, to avoid getting into anundefined state of log(0) a constant 1 is added to all input pixels. The constant C serves as a variable used for adjusting the image enhancement level. Figure 7 below shows the effect of varying the value of C on the contrast level [37].

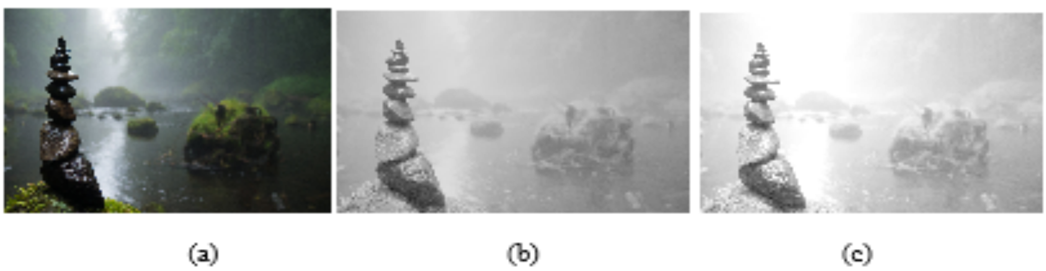

Figure 7: Logic transformation enhancement technique.

(a) Original image (b) Output with constant C = 0.3 (c) Output with constant C = 0.45

3.4 Image Segmentation Process

Image segmentation, as the name implies, is the process of dividing an image into smaller parts namely segments. The technique is carried out in order to isolate an object or region of interest (ROI) from the image background, hence separating the meaningful and most important region for easy analysis [20,38]. Segmentation to be precise helps in simplifying an image using a specially designed software. It is commonly used in the areas of image compression and object recognition [19, 42-45, 48-54]. Quite a number of segmentation methods exist and are categorized based on image characteristics such as the pixel intensity value, color, textures etc. These techniques are broadly classified into Edge based, Region-based and Pixel based. The edge-based is further classified into Active Contour and Edge Detection. The Region based is divided into Graph cut, Merge/split, while the Pixel based is categorized into Clustering, and Thresholding, which is further, divided into Fuzzy C-Mean and K-Mean for the Clustering and Global and Adaptive for Thresholding. Figure 8 depicts the block diagram representation of the various image segmentation techniques. Table 1 below summarizes the various segmentation techniques used in wastewater treatment. The sole objective of segmentation is to group image pixels into salient image territory that represent individual surfaces, objects, or natural parts of objects. To segment an image using Thresholding and obtain a good result, the ROI is declared manually with the aid of a mouse [38]. Then the image is segmented using a predefined threshold value with value 1 taken as the object and value 0 is the background. The process can be performed manually or automatically. Figure 9 illustrates a physical example of an image that has been segmented using Thresholding.

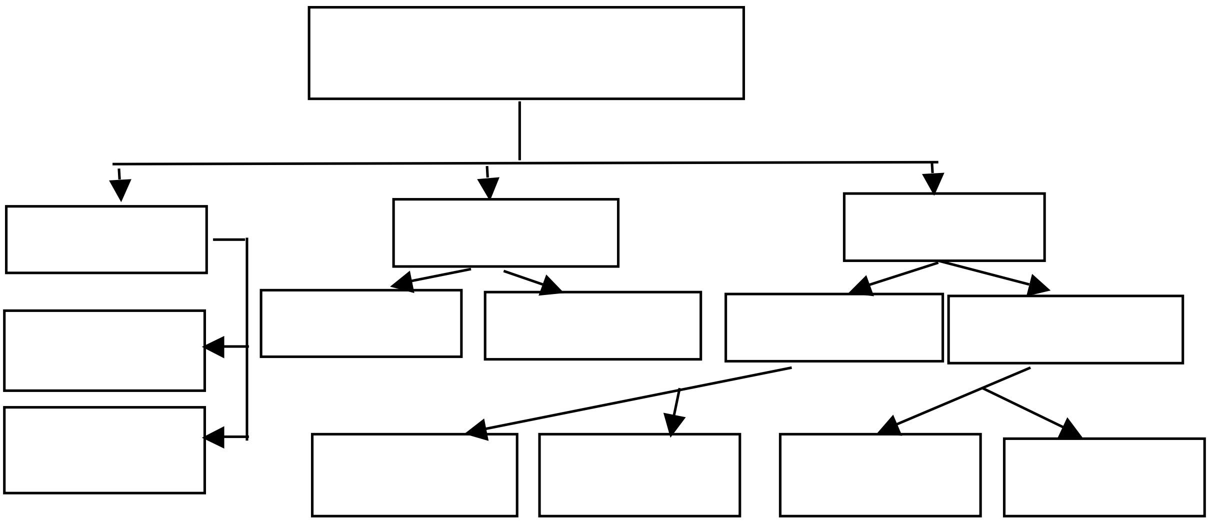

Figure 8: Image Segmentation Techniques

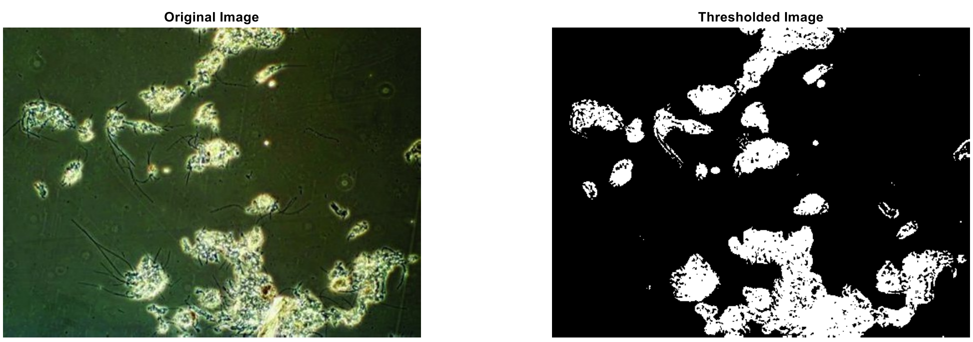

Figure 9: Comparison between normal and segmented image

3.5Image Analysis

Image analysis is the process of extracting meaningful information from the digital image. The information extraction could be automatic or semi-automatic methods termed scene analysis, image description, image understanding, pattern recognition computer/machine vision. Unlike other image processing method that deals with the image to image transformation, for image analysis it deals with the image to numerical outputs [39].

3.5.1 Wastewater Characteristics Image

In order to use image processing for wastewater quality detection, sample image characteristics need to be analyzed and studied. Image analysis and characteristics of wastewater have been used to monitor and control activated sludge wastewater treatment plants and other industrial waste plants like ternaries, breweries etc. As outlined earlier, some standard measurement for wastewater monitoring related to active sludge mixed liquor suspended solids (MLSS), effluent chemical oxygen demand (COD), and Sludge Volume Index (SVI) [40]. The process of characterization of filaments and flocs using image processing become easier and fasterdue to the automation of the process [41]. Three abnormal conditions i.e. formation of viscous or zoogleal bulking (ZB), filamentous bulking, and pinpoint flocs (PP) can be identified using image analysis procedure [22]. The wastewater image processing techniques used in various studies are summarized in Table 1 below.

Table 1: Summary of previous research

References	Research summaries
[19]	▪ To assess activated sludge settleability and concentration level. ▪ Uses CCD camera as the image acquisition device with dark field microscope and x50 magnification value. ▪ Employs thresholding segmentation technique and uses Microsoft visual C++ as processing software.
[42]	▪ To characterize and quantify the number of flocs formed due to protozoa in the wastewater. ▪ Uses CCD camera for image acquisition with phase contrast microscopy and x400 magnification value. ▪ It is considered semi-automated due to manual threshold declaration in thresholding segmentation with vision 5.1 processing software.
[43]	▪ The study aims at detecting flocs and filamentous bacteria in the activated sludge. ▪ Employs joint detection of fractal dimension operator and separate detection using variance and Laplacian of Gaussian operator. ▪ Uses bright field microscopy with CCD video camera. ▪ The researcher was able to achieve the aim with a few inaccuracies attributed to poor illumination. ▪ The result shows fractal dimensions can be used to perform texture-based image segmentation.
[44]	▪ The paper characterizes the activated sludge base on flocs and filamentous bacteria size and shape in a pilot-scale reactor. ▪ It acquires macro and mesoscale images using the bright field (optical light) microscopy and video camera at x100 magnification. ▪ Uses visilogTM5 software for the image processing and analysis.
[45]	▪ The paper established the relationship between sludge volume index (SVI) and filament fraction in a laboratory-based sludge replica. Giving significance to early detection of bulking. ▪ Characterize floc based on size, shape, structure, and distribution of the sludge. ▪ Assess the transformation of micro-flocs with and without toxic substance. ▪ Uses bright field microscopy with 10X magnification and coupled with CCD video camera. ▪ Uses histogram equalization to enhance the image contrast. ▪ Employed both pixel-based (thresholding) and edge-based segmentation techniques.

[46]	▪ Developed a fully automated image processing technique that assesses five descriptors (aspect ratio, roundness, radios of gyration, form factor and fractal dimension) capability of identifying (characterized and quantify) flocs and filament from the processed image. ▪ Uses phase contrast microscopy at x100 magnification level with a CCD camera. ▪ Employed Thresholding segmentation technique using Matlab image processing tool as the software.
[47]	▪ An extension of the previous methodology carried out in a lab-scale installation by Jenne*et al*.[46]. ▪ Conducted a 100 days experiment where the result (processed image data) tends to correlates well with the tank sludge volume index (SVI).
[48]	▪ Uses Bright field microscopy with a video camera at x100 magnification factor. ▪ Uses histogram enhancement technique and Threshold algorithms for segmentation with VisilogTM image processing software. ▪ Developed an automated system that uses the gram-stained technique to monitor the characteristics of filamentous bacteria in laboratory scaled experiment. ▪ Changes the Gram-image from Red, Green, Blue (RGB) pixels to Hue, Intensity, Saturation (HIS).
[49]	▪ Employ image analysis to quantitatively monitor through recognition and quantification the dynamic changes of aggregates in the anaerobic sludge. ▪ Uses both phase contrast and bright field microscopy for filament and aggregates processing with CCD camera at x100 and x4 magnification respectively. ▪ Employs Scanning Electron microscopy (SEM) to visualize the aggregate surface. ▪ Uses histogram equalization and the threshold for enhancement and segmentation and Matlab software for analysis.
[50]	▪ Applied image-processing technique to assess the competition between filamentous microorganism (FM) and non-filamentous bacteria (NFB) in a stirred tank reactor. ▪ Employed phase contrast microscopy with CCD camera at x1000 magnification. ▪ Both experimental and simulation results show that the proposed mathematical model performs in well. ▪ Uses histogram equalization and the threshold for enhancement and segmentation and Global Lab image 2.10 for analysis.
[51]	▪ Studies the effect of floc characteristics ondewaterability of activated sludge. ▪ The floc properties considered are physical, morphological parameters, chemical composition and extracellular polymeric substances (EPS). ▪ Translate dewaterability to bond water content and the capillarity suction time (CST) of the activated sludge. ▪ Among all the characteristics considered, physical properties have the most significant effect on the sludge floc water-binding ability.
[52]	▪ Surveyed the sludge morphological properties such as total suspended solids (TSS) and sludge volume index (SVI). ▪ Uses partial least square regression (PLS) to establish a correlation between TSS and total aggregate area. ▪ It also establishes a strong relation between filamentous bacteria per suspended solids ratio and the sludge volume index (SVI). ▪ Uses phase contrast microscopy on Zeiss Axioscop microscope with x100 magnifications for filaments, while Olympus stereo microscope with x40 magnification for the aggregates both scope uses CCD video cameras for capturing ▪ In both cases, histogram equalization and threshold enhancement were perform using Matlab 6.5 software.

[40]	▪ Uses image analysis information (i.e. form factor, roundness, the radius of gyration etc.) to detect early formation of filamentous bulking. ▪ Uses a number ARX black box model to model the sludge volume index (SVI) to predict the onset of filament formation. ▪ Carried out the experiment in a lab-scale activated sludge setting with Olympus BX51 microscope and video camera for image acquisition at x10 magnification level. ▪ Uses Matlab toolbox for processing and analysis.
[53]	▪ Uses image analysis to characterize three different wastewater treatment plants based on microbial floc. ▪ The paper analyzed and established a relationship between the morphological parameters such as the diameter, compactness, roundness, porosity and fractal dimensions. ▪ Uses bright field microscopy with a photonic microscope and Nikon CCD camera at x120 magnification level for image acquisition. ▪ Uses both histogram equalization and median filtering enhancements and Zack algorithms for segmentation all performed on image Pro-Plus version 4.5.
[54]	▪ Developed an online digital image analyzer (DIA) that simultaneously measure particle size distribution and morphology in wastewater treatment plant. ▪ The particle size distribution obtained by the DIA analyzer is similar to that of laser analyzer proving the DIA efficacy. ▪ The obtained DIA measurements, when combined with the artificial neural network (ANN), enables the precise prediction of the number of suspended solids (SS) concentration and precipitation levels. ▪ Uses micro-lens and halogen illuminator coupled with CCD camera. ▪ Uses lookup tables, convolution and media filter for image enhancement and entropy and binarization for segmentation all in NI vision assistant software package.
[22]	▪ Predicts mixed liquor suspended solids (MLSS) and sludge volume index (SVI) parameters under normal condition and different kinds of activated sludge disturbance. ▪ The experimentwas conducted for filamentous bulking, zoogleal bulking, pinpoint floc formation and normal condition. ▪ For the four experimental setups, the relationship between filament total length per volume (TL/vol) and aggregate total area per volume (TA/vol) with that of (TL/TA) and (TL/MLSS) were graphically sketched. ▪ Both brightfield and epifluorescence microscopy was used for image acquisition using Olympus DP25 camera at x100 and x200 magnification level respectively. ▪ The enhancement and segmentation programs were ran using Matlab 7.3.
[55]	▪ Particle image velocimetry (PIV) was used for morphological characterization and for velocity data acquisition from a coagulation process of a reactor. ▪ The study correlates the rotating speed with the flocculation efficiency and floc size. ▪ The technique is suitable for in-situ monitoring of flocs during coagulation. ▪ The PIV system comprises of Taylor-Couette flow apparatus, double pulsed ND-YAG laser, CCD camera, flow map system, the host computer and special PIV software.
[56]	▪ Uses image processing technique to characterize and quantify flocs morphological parameters (shapes and size) of activated sludge operating at normal condition. ▪ Needs to investigate floc characteristics under dynamic operating conditions. ▪ Uses Olympus BX 41 microscope with CCD camera at x40 magnification level. ▪ Employs Matlab software for image analysis.
[57]	▪ Uses three sets of segmentation techniques to detect flocs in domestic activated sludge. ▪ Uses bright field microscopy to acquire the image with different magnification level and the image is passed through segmentation without enhancement. ▪ The performance of the three segmentations (Otsu thresholding, K-mean, and fuzzy c-

	mean) at different magnification level was assessed. ▪ Otsu thresholdingwas found to the best segmentation based on global consistency error (GCE) and better in terms of floc quantification then other algorithms.
[58]	▪ Analyses the activated sludge morphological parameters (roundness, compactness etc.) ▪ Proposed new segmentation algorithms to be used for both flocs and filament. ▪ Compare the result obtained against laser particle analyzer, where laser appeared to have better accuracy in estimating the floc and filament size. ▪ Use Zeissprimostar microscope with CCD camera for acquisition at x4 magnification. ▪ Uses the new segmentation technique with median filtering as contrast enhancement in Matlab software package.
[59]	▪ Uses images acquired through satellite to assess the water quality. ▪ The quality was assessed by comparing the acquired image histogram matching to that of a known clear water quality that is considered the standard. ▪ Depending on the Euclidean distance between the two histograms, the water purity level is considered to be excellent, better, good, bad or poor. ▪ Uses MultiSpecwin 32 software to perform the ISODATA clustering algorithms that separate the water from other bodily features.
[60]	▪ Proposed a segmentation technique with illumination compensation for image processing technique of activated sludge. ▪ Uses bright field microscopy and global Otsu thresholding algorithms. ▪ The integrated illumination was modeled and estimated using Gaussian distribution. ▪ The proposed algorithms were measured against time spent for segmentation, Rand index, accuracy and quantification of floc. ▪ The algorithms prove to have better performance when compared toSauvola and Bradle's algorithms.
[61]	▪ The paper uses bright field microscopy with four integrated image segmentation techniques to estimate the sludge volume index (SVI). ▪ The images were acquired using Olympus CCD camera at x4 magnification level. ▪ The four algorithms were integrated using OR to avoid failure and are implemented using Matlab R2013b. ▪ The findings show that image analysis based modeling having six parameters can be used to predict the SVI.
[9]	▪ Proposed a generalized classification model for the activated sludge that does not require prior information about the plant and it states. ▪ It operates based on the morphological parameters extracted from the flocs using bright field microscopy. ▪ Proposed a support vector machine (SVM) with a new agreement solver for imbalanced data of activated sludge plant. ▪ Using the performance metrics the classification results obtained are compared against the start of the art SVM and ensemble classifiers. ▪ The proposed method shows better performance by identification of different plant states.

3.5.2 Satellite Images and Embedded System

Apart from computer-based imaging that uses the camera for image acquisition in wastewater treatment monitoring, there are also satellite images and embedded systems. Histogram method is one of the techniques used for measuring water quality through satellite imaging [59]. The technique involves comparing the captured image parameters against a known clear water standard parameter. The sampled image clear water body is been separated from other features by means of clustering, which is then used as standard and its number of pixels in percentage is also counted. Those images, which contain the same percent of water bodies as the perspective standard ones, are being verified by comparing their histograms. The Euclidean distance between the standard and sampled image histograms is measured. Depending on the distance obtained, the water quality is considered to be either excellent, better, good, bad or poor based on their degree of purity [59]. High and medium resolution satellite data can be acquired and drive into digital values just as in the studies reported by Muhairi et al., [62]. They use satellite data to calculate spatial variability and average digital value around Jebel Ali plant in Dubai. In 2008, the spatial variability surrounding Jebel Ali plant was acquired using Dubaisat-1 and MODIS for image and data acquisition. Between January and December same year, field temperature data was collected. The acquired field data and the one acquired through satellite-derived sea surface temperature (SST) were compared and analyzed. There is a strong correlation between the two different sets of results. To further enhance the result analysis, the author calculates the peak signal to noise ratio (PSNR) and mean squared error (MSE) [62].

Embedded system usingAshton Raggatt McDougall(ARM)can be integrated with an image sensor and light intensity to acquire sewage image to be used for characteristic image analysis. The acquired image is processed using edge detection algorithm and image enhancement. ARM system uses image-processing algorithms to determine the quality/purity level of sewage water in the treatment plant, this provides the decision whether to discharge it into the environment or it needs to be re-purify again. It operates based on image detection algorithm and light intensity information [63].

4 Automated wastewater quality detection by image analysis

An important aspect of this type of wastewater quality detection system is the early quality detection. This will serve as an early warning if any of the quality indicators has exceeded the set limits before the treated wastewater is released into the environment.

In order to detect wastewater quality, a vision system is put in place to take a photo or acquire an image of some visible wastewater parameters; in most of the cases is the activated sludge in the wastewater. Khan et al. [64] mentioned that the acquired and analyzed image has been used to monitor the activated sludge in the wastewater treatment plant.

To provide a better monitoring of the wastewater quality, there must be a system that can continuously monitor the wastewater quality without depending on human intervention, which is subjected to misinterpretation and tiredness. The system may be connected to an online system, for example, a Supervisory Control and Data Acquisition SCADA system or can be automated through vision-based system and analysis, reporting and action made online through the internet. The real idea behind this is to reduce human intervention thus providing a continuous monitoring [63].

4.1 Real-Time Quality Monitoring System

Online monitoring is a real-time and in situ monitoring of quality at the wastewater location in contrast to collecting quality indicator samples and transporting them to the laboratory for photo taking, in order to acquire the digital image of the samples. There is no contact between human and wastewater. Therefore, the use of human laboris minimized and monitoring cost can be reduced.

A good online wastewater quality monitoring system must be capable of monitoring multiple quality indicators at the same time, integrated, economically and can be used easily. In this case, for visible quality indicators, the image must be able to be acquired online in real-time so that analysis can be done automatically and the result obtained instantly can be used to provide quality indicators.

A comprehensive online digital system was first built by Yu et al.,[54] which contained both monitoring and analyzing system with user-friendly i/o ports. It comprises of a CCD video camera that uses microlens together with a magnetic pump for online measurements. This system monitors and measures particle size using particle size analyzer. The system then acquired digital images that are analyzed with digital image analyzer to measure the diameter of the particles. The computed particle sizes are obtained in terms of distribution with the difference in peaks of almost similar shape. The analyzer then finds the linear relationship between fractal dimension and precipitation efficiency.

Nguyen et al., [65] used a video camera for online monitoring of a sewage water quality level and obtained the images of the sewage water. The images obtained online are processed in parallel using image processing algorithm and the processed images are compared with the local database to obtain the result. This online measuring device is quite accurate making investigation able to be done off-line.

4.2 Automated Image Analysis Vision-based System

Hein et al.[66] found that by automatically analyzing the microscopic picture of activated sludge samples, it would enhance the operation control of the aeration tanks by introducing a new sum parameter. Using the processed sludge images thus performing the statistical evaluation, several parameters are enough to describe the activated sludge flocs characteristics alteration.

Ginoris et al. [20] developed a semi-automatic image identification and analysis system to detect two types of bacteria typically present in the activated sludge of wastewater treatment plants, namely the protozoa and metazoan species. They used LeitzDialux 20 optic microscope coupled to a grey scale video camera Hitachi CCTV HV-720E(F) (Hitachi) to acquire the image of the species. The system consists of image processing and statistical analysis, which leads to the application of morphological descriptors utilizing discriminant analysis and neural network techniques. In this system, MATLABsoftware was used to recognize the protozoa and metazoa and the image analysis program written in MATLABhas proven to be adequate in doing the identification job.

4.3 Web-Cam Based System

Several studies have discussed in details the advantages of using biological means for specific treatment of wastewater components and hinted the possibility of improving the quality of such methods by incorporating web-based monitoring techniques. Using RGB web-cam, Jeon et al., [67] developed a biological early warning system (BEWS). The system is equipped with six monitoring channels to individually observe the activity of Daphnia Magna. The acquired images are displayed on a monitor with a digital 'Grid Counter'. The monitor showing the 'Grid Counter' with digitized images would trigger an alarm within an appropriate time. The researchers, by observing the displayed images with alarm trigger, have examined the functional performance of the developed BEWS and found it suitable for detecting unusual wastewater quality.

Conclusion

It can be deduced that the need for an effective, reliable and easier alternative means of monitoring the quality of both our domestic and industrial discharges was triggered by the challenges faced by the earlier techniques. The advancements were achieved in a gradual phase-by-phase process, from laboratory electronic sensors to autonomous online (In-situ) based acquired sensors and flow analysis techniques that are remotely monitored using Supervisory Control and Data Acquisition (SCADA) software. These techniques were limited to a certain number of indicators and suitable for specific environmental conditions and settings. The advent of image processing techniques further enhances and improves the detection of many parameters, hence, broadening and extending the area and field of applications. The quality is better than the classical.

The breakthroughs made so far in image analysis and characteristics of wastewater have yielded significant positive outcomes and improvements in the overall quality monitoring performance. Thus, computer-based imaging can now be used in the online or offline systems depending on the plant size and location. For online systems, the system needs to be near the plant, hence making it suitable for relatively small areas. For large area coverage, satellite imaging is the recommended practice, where the high expenses incurred due to data-cost, poses a disadvantage. As for the embedded system, the system can be used in far and hard to reach areas.

This study also reveals that automated or autonomous (intelligent) quality indicators differ from the online monitoring system in the sense that for the online monitoring system, it still requires human intervention to analyze and interpret the processed image and decide on the quality whether the wastewater condition satisfies the stipulated limits. The autonomous quality indicator, on the other hand, can automatically analyze the image, process and interpret the results. Then it could make the decision on the quality of the wastewater by itself with minimum or zero human interference.

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