The Effectiveness of the Semi-Automatic Technique in Extracting Shoreline from Digital Elevation Models for Sustainable Development in Africa

Mitchell A. Eboigbe, Amos Ugwuoti Amos and Anthony A. Sam

ABSTRACT

The accurate delineation of Shorelines is required to determine the respective tidal heights and monitor coastal erosion. In some coastlines, the difference between the high tide and the low tide could be as small as one meter but the accurate extraction of the respective vertical surfaces is required to understand the pattern of the sea wave energy and to chart tidal heights relative to a specific datum. The manual digitizing of shoreline is usually with high accuracies and flexibilities but could be rigorous and hectic especially for longer shorelines. Automatic extraction is more feasible where the wavelength intensity gradient within a sub-pixel level is at maximum for instantaneous shorelines with small tidal range. This is due to topological inconsistencies that could hinder such accuracies. In this study, an improved mean shift segmentation model extracts shorelines from digital elevation models from LiDAR and a UAV survey. The key element of an accurate DTM is the contouring network capable of delineating between the grid pixels each representing water and land whose elevation is below or above tidal datum. The study locations are the Freshwater and the Perranporth bay in the United Kingdom. The third is the Nigeria Maritime Academy Oron shoreline. The choice for the different study areas is to ascertain the reliability of this technique on different geographies. Comparison between manual digitizing and the mean shift segmentation were both by visual interpretation and by volumetric change analysis for two different years. The results obtained indicate that the mean shift segmentation can delineate tide-coordinated shorelines accurately. The limitation of this methodology is on digital images with poor spectral resolution. Recommendations include the use of this technique on open source GIS software and a practical solution to developing a monitoring infrastructure for coastlines in Africa.

Keywords: Shoreline extraction, Semi-automatic, Tidal heights, Coastal Monitoring.

I. INTRODUCTION

The shoreline is a radically distinctive feature with vital information for coastal, engineering, and environmental planning [1], [2]. Every national development would include considerations for coastal areas due to global warming and associated challenges [3]. As of 2010, more than half of the world populations live within 100 km to the low-elevation coastal flood risk zone [4], [5]. In Nigeria, more than 25 million people have lost their homes due to coastal flooding [6]. The shoreline is an elevation surface that differentiates between the bodies of water from the land [7], [8]. Shorelines are typically geometrical and fundamental to illustrate coastal morphology [9]. Accurate delineation of shorelines is vital for evaluating earth gravitational displacement [10], legal boundaries [11], [1], and coastal flooding and erosion [3]. Aerial photography, satellite, and optical remote sensing, land surveys are existing methodologies for shoreline detection and management [4]. The cost, resolution, and frequency of surveys limit the applications of these techniques [12], [13]. High-resolution large and medium scale digital photogrammetric techniques can now develop an accurate and reliable data source for shoreline monitoring [14], [15]. Similarly, the traditional manual digitizing of shorelines characterized by constraint in the change of scale, in contemporary times has metamorphosed into automatic and semi-automatic shoreline extractions [16]. Irrespective of the field and data processing technique, the magnitudes of changes along the shorelines rely on analytical methodologies referenced to some adopted ground control network [3] that integrates changes into a composite mapping system for sustainable development. The focus, therefore, is to boost the accuracies of the geodetic measurements and improve on the analytical representation of the morphology and respective vertical heights along the coastlines [17].

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A. Shoreline Extraction as an Analytical Framework for Sustainable Development

Accurate and regular delineation of vertical surfaces along the coastline is crucial to generate a geospatial framework for geodetic and mapping purposes [18] as required for sustainable development. Regular charting of the land and sea separation will help hydro-morphological infrastructure for the physical and biological status of the seas [19]. Shoreline extraction is required at very high accuracy to integrate change(s) into a ‘dynamic environment’ [20], [21], and to boost social and economic activities [22]. Shoreline data management has now become a prerequisite for maintaining the water harbour, territorial defense, agriculture, historic preservation, navigation, and even sporting [23]. Legal boundaries and Maritime zones are best described and mapped by reference to tide coordinated shorelines [24], [25]. Shoreline monitoring will help determine cost-effective, social, and environmentally friendly mechanisms for coastal floating and erosion control [26]. Modern strategies for optimal land reclamation include spatial considerations for the shorelines [25]. Shoreline management also ensures the development of a general environmental policy framework for sustainable development [26], [3].

B. Review of Existing Methodologies

Every methodology for shoreline extraction must consider the physical domain or been projected to some specified and accurate mapping system that integrates a framework for sustainable development [19]. Robustness is fundamental in developing a technique for shoreline extraction from LiDAR and other high-resolution images [7], [23], [7] expatiate the “objectivity and automaticity”. There are several other shortcomings in methods proffer by recent studies but the objectivity which is often a function of the definition of the shoreline determines the aim for the method adopted [23].

Existing shoreline algorithms conform to some characterization of the coastline and each depends on the data type been analyzed [4]. The manual digitizing of shorelines is more accurate as it involves an analyst who inputs seed-point linearization relative to a change in scale [24]. Shoreline extraction is accurate and reliable for every image type with manual digitizing although low image resolution could reduce digitizing accuracy [27]. Manual digitizing of shoreline could be accurate but very hectic, time-consuming [27] and requires carefulness during digitizing. This might not be too useful in very long coastlines that require regular monitoring. The performance of algorithms for automatic shoreline extraction varies with image resolution [26], [28]. Variations in spectral resolution as caused by shadows, interceptions from other features like trees, water hyacinth also hinders the accuracies of the automatic extraction techniques on satellite imageries [29]. Automatic algorithms are more effective in digital elevations due to the contouring network capable of delineating between the grid pixels whose elevation is below or above tidal datum representing each ‘water’ and ‘land’ [30]. It is difficult to obtain tide-coordinated shorelines from aerial photogrammetry [3] and this limits the accuracies of the several algorithms on aerial imageries [30]. Automatic detection of shoreline change on high-resolution satellite imageries is more practical therefore as satellites cover larger areas and can now provide a repetitive coverage of 1 to 3 days [31]. However, these algorithms for automatic extraction of shorelines conform to specific spectral propensities [4]. The scale and offset algorithm will improve the accuracy of the rational function coefficients on IKONOS and other high-resolution satellite imageries [16]. The wavelength transform splits signals at different scales [7]. The thresholding segmentation models are to improve on the classifications of panchromatic images [4]. High-resolution satellite imageries, LiDAR and aerial images are expensive and lack the temporal resolution required for some geographical locations.

The refinement of shoreline by removing “spurious segments” using the semi-automatic segmentation method is effective [32]. A comparative evaluation of the semi-automatic technique and the manual digitizing of shorelines are in [11]. Semi-automatic segmentation allows for manual checks and refinement [16]. In the mean shift segmentation, pixels, and its colour in space (L*U*V*) are clustered into nodes to generate delineation [33]. The semi-automatic algorithms are less expensive as compared to the automatic algorithms. The process is virtually computer-aided which makes it not as burdensome and time-consuming as with manual digitizing. The disadvantage with the mean shift segmentation is that it depends on a sampling class with a well-defined spectral characterization [34]. In this study, we improve on the refinement of the spectral characterization by segmenting the image before and after the kernel densities. This helps to improve on the convergence of the clustering of the nodes as required for delineation [33].

C. Statement of Problem

Coastal Monitoring and management would involve constant evaluation of the several vertical surfaces [26]. The several other coastal geomorphologies would also require segmentation for specific scientific analysis and engineering purposes [3]. These monitoring programs for sustainable development are required regularly. The manual on-screen digitizing is stressful and time-consuming. Existing algorithms for automatic extraction of shorelines do not apply to digital models from several data sources. A semi-automatic methodology that would be applicable for several digital elevation models and accurate to delineate the different elevations along the coastline is required therefore for an analytical framework of national development.

II. STUDY AREAS

The study areas are two different shoreline geographies in the United Kingdom and another shoreline location in Nigeria. The freshwater bay is within the unitary authority of Isle of Wight. It is in the southeast of England. This shoreline measures about 1.4 km and known for its cliff that collapsed on 25th October 1992. Its geographical coordinate is 50.682566°N and 1.524884°W. The Perranporth is at the Unitary authority of Cornwall and measures about 5km and it is in the southwest of England with coordinate 50.3437°W and 5.1546°W. The Maritime Academy of Nigeria (MAN), Oron Akwaibom State, Nigeria lies on Latitude 04° 48″ and
on Longitude 08° 14′ and used to access the viability of this methodology on the Nigeria perspective and a different shoreline type and geography.

III. METHODOLOGY

In the mean shift segmentation, there are two main operations used to determine the desired class boundary. The first is the filtering of the point feature image to the approximate class group and the second is the clustering into the desired class boundary using a controlled feature mask. According to [35], a “non-parametric classification” simply moves the kernel centre to fits the desired class in the mass distribution.

\[ M_i(x) = \frac{\sum_{i=1}^{n} K \frac{x - x_i}{h}}{\sum_{i=1}^{n} K \frac{x - x_i}{h}} - x \]

\( i = 1, \ldots, n \) for a given input feature points. Points are added only in the cluster sum if they fall into the desired radius within (x, y) geo-location [26], [16] [36]. K is the kernel density while h is the bandwidth of cluster.

This study improves on the methodology developed in [35] by introducing an initial neighbourhood after the kernel density. This is to accommodate for better clustering from different image resolutions and data types. Another advantage of introducing an initial cluster window is to fasten the segmentation process, as the mean clustering could be slow with the point feature data [37]. The improved workflow is:

1. Convert the digital elevation model to a point floating data. At this stage, a point of \((L^*, u^*, v^*)\) is created at the centre of each raster cell as \((R, G, B)\) are relative to the shape and size of each raster cell.
2. Create a kernel density from the point data with an already defined radius. This will help to segment the different digital elevations on the image.
3. Create a new shapefile by polygon around the class of interest from the kernel density created in step 2.
4. Extract the class of interest from the kernel density using the “extract by mask spatial analyst tool” and the new shapefile by polygon as the “input feature mask data”. At this stage, the \((L^*, u^*, v^*)\) at the cluster mode is converted to \((R, G, B)\).
5. From the table of content on the symbology on the layer properties, remove the other layer, which does not fall into this desired centre of mass.
6. Altering the class range by manual classification will match to match the shoreline as desired.

Steps 1–6 can be written as a python script for automatic shoreline extraction. For this study, the aim is to develop a semi-automatic process that is more flexible, cheaper, and applies for the segmentation of other regions of interest along the coastline for sustainable development. The evaluations were to assess the change along the coastlines from 2008 to 2012 in the Freshwater and Perranporth bay, respectively. LiDAR was downloaded from the channel coast observatory website. All spatial analysis was in ArcMap 10.1. Figures D and E illustrate the kernel density with the defined radius. LiDAR and aerial images downloaded were for 2008 and 2012. One of the objectives of this study is to evaluate the workability of this technique on different geographies and images obtained from different remote sensing sources. The freshwater bay is mainly undulating with cliffs. There could be further adjustments to the kernel outputs. For this study, no on-screen digitizing or morphological corrections were used to adjust the outputs. Volumetric change analysis from the outputs of the mean shift segmentation and the manual digitizing helped to validate the reliability of this improved mean shift segmentation for an analytic framework of the coastlines.
IV. DISCUSSION OF RESULTS

A. Visual Comparison between the Shorelines Extracted using the Mean Shift Segmentation and the Manual Digitizing

1. Fresh Water Bay (2008 – 2012)

The manually digitized shoreline on the LiDAR corresponds with the semi-automatic shoreline except in a few areas there is the shadow cast from the cliffs as shown in regions A, B, and C below. In regions, B and C, were the MHW is difficult to discern visually, the accuracy of the mean shift segmentation also reduced.

2. Perranporth Bay (2008 – 2012)

The Perranporth is relatively a flat dune coastline. The results obtained from both techniques are almost the same. On the difference map, both shorelines are the same. Region B has dashed cut as indicated by the black line (2012) intercepting with the yellow (2008). Region A and region C are with the same curve and pattern distribution between the shorelines and their cut and fill.
B. Volumetric Change Analysis

1. Fresh Water Bay (2008 – 2012)

There is a reduction in both the width and the area of the MHW. This implies a decrease in volume as shown in the frequency table. The yellow line (2012) has reduced slightly between the four (4) year periods. The computation that tallies with the visual inspection shows that the mean shift segmentation is effective for monitoring undulating terrains.

2. Perranporth Bay (2008 – 2012)

Between the years 2008 and 2012, the MHW increased in volume by a minor percentage except for a few locations as seen on the frequency table. The mean shift segmentation is also very effective to monitor the flat coastlines.

C. Shoreline Change Analysis in Nigeria

A UAV survey was in June 2017 using the DJI Phantom 3 standard to generate a digital elevation model for the shoreline at the Nigeria Maritime academy, Oron. The GNSS survey was before the drone survey using the Promark 200 dual-frequency in real-time kinematic mode. The geolocation accuracy of the orthomosaic and digital elevation model was 2cm at both the vertical and horizontal with a spatial resolution of 7mm. The result of the manual digitizing and the segmentation is in figure 12 below. The mean shift segmentation was more accurate on the MHW than the MLW. The separation between water and land on the MHW is mainly by water plants and other sea debris with a better spectral reflectance compared with the MLW that is by a dune. This model can be used therefore to generate a shoreline-monitoring infrastructure for both geodetic and environmental monitoring along the Oron coastline using the digital photogrammetry as the data source.

V. CONCLUSION AND RECOMMENDATION

The methodology is effective to extract shorelines from all coastal geographies. Limitations on the accuracies of this methodology are with the shadow cast and poor spectral quality. This methodology is viable with digital elevation models due to conversion into digital point feature data. The entire process is possible on the Quantum GIS that is open source. Digital images do not only provide accurate measurements and delineation of the coastlines, but they are also very vital for visual interpretation of the coastline. The application of close-range digital photogrammetry for coastal monitoring is therefore very practicable and low-cost technologies for the analytical framework of sustainable development. A robust and repeatable field technique and processing routine will help develop a more realistic methodology for coastal monitoring [23]. The duo of the mean shift semi-automatic segmentation and digital photogrammetry will generate into a coastal geospatial data infrastructure. The MHW in most cases is more stable and defined than the MLW especially in rugged terrains like with the freshwater bay. The tide-coordinated shorelines are most appropriate for shoreline data management. According
to [23] “the remaining challenge is to improve the quantitative and process-based understanding of these shoreline indicator features and their spatial relationship relative to the physical land-water boundary”.

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