A PROJECT PROPOSAL ON FEATURE EXTRACTION, CLASSIFICATION AND MULTI-CLASS ERROR ANALYSIS OF SEWER PIPELINE IMAGES

Introduction:

Civil infrastructures play an important role in the development of a country's economy. The infrastructure cost in the US alone is more than $20 trillion [1]. According to the American Society of Civil Engineers' (ASCE) report, there are an estimated 0.7 to 0.8 million miles of public sewer mains in the United States [2]. Many of these pipelines were installed after World War II and are aging down. Due to the inadequate human resources, not every section of the pipe gets the required attention. Operational and maintenance cost of these pipelines itself requires billions of dollars every year. An irregular and non-periodic trend of sewer-pipe inspection jeopardizes the structural integrity of the waste water mains, thus increasing the possibility of untreated sewage discharge into the surroundings. A novel and innovative approach to classify healthy and unhealthy water mains is required to reduce human intervention. This system can improve the decision making ability based on objectivity, rather than on a subjective human perspective. This proposal includes feature extraction, classification and error analysis of sewage mains.

Problem Statement:

Terabytes of videos are recorded by sending unmanned vehicles into sewer pipelines. Analyzing these videos requires experienced human inspectors and hours of laborious visual inspection. In general, visual inspection by humans are very subjective. A damaged sewer pipe can induce a threat to the ground water sources and can be responsible for environmental issues and spread of epidemics.

Objectives:

Our current database consists of gigabytes of recorded sewer-pipe videos. As the first task, hundreds of these videos have to be converted to images, followed by the preparation of a sample dataset. A sample dataset consists of training, validation and testing images.

After obtaining the image dataset, a few pre-processing algorithms such as image in-painting (text removal), super-resolution and denoising are to be performed. Feature extraction involves using Eigen value decomposition of a Hessian matrix to obtain curvilinear features [3]. Additionally, information of the image color space, its distribution and general shape characteristics such as circularity, area and others will also be considered. Once the features have been obtained, key features are selected by using Sparse Principal Component Analysis [4].

Defective and non-defective characteristics of sewer-pipe will be classified by using well known classifiers such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), Random Forests and Adaptive Boosting (AdaBoost). These will be implemented using open-source libraries. Roughly, 3 to 8 classes will be considered in this work, namely: pipe-joint, pipe intersection, corrosion and others.

Out-sample error analysis based on the Vapnik-Chervonenkis (VC) dimension for a 2-class problem will be generalized to the multi-class case [5][6][7]. This theoretical out-sample error (from the VS-dim) will be compared with an empirical value obtained from the population. A classifier among the ones being considered will be chosen based on the results of the error analysis.

References:

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