A New Image Model for Predicting Cracks in Sewer Pipes based on Time

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ABSTRACT
Sewer overflows may cause communities to be vulnerable to various health problems and other monetary losses. This puts a lot of burden on responsible to minimize end user complaints. Therefore, crack prediction would be helpful to facilitate decision makers to control sewer overflow problems and prioritize inspection and rehabilitation needs .The accurate prediction of current underground sewer pipe cracks must be done before any pipe crashing with enough period of time to enable rehabilitation and replacement intervals, appropriate remedial methods and preventing sewer pipes crashing. Unfortunately, traditional technologies and models approaches have been limited to predict the development of sewer pipe cracks. In this paper, we address the problem of crack prediction of such cracks. This paper provides a proposed model which predict crack and cracks developments in any period of time that may occur in weak areas of a network of pipes.. We evaluate our results by comparing them with those obtained by many other models. The accuracy percentage of this model exceeds 90% and outperforms other approaches.

Keywords
Pipe crashing, Sewer pipes, rehabilitation, Crack prediction, cracks developments, sewer pipe inspection ,sewage rehabilitation

1. INTRODUCTION
There is an urgent need to develop a proactive sewer pipeline crack prediction model. Due to the fact that sewer pipelines are hidden from day to day view, deterioration can occur unnoticed and this can in turn lead to unexpected functional failures. Moreover, maintenance and rehabilitation of aging sewers have become an overload in terms of budget allocation and investment planning for towns [1]. Multiple objectives may exist for planning budget allocation that could be dependent upon certain constraints and available resources. This makes the task of planning, prioritizing and allocating funds a complex exercise [1].

The failures of pipes can cause serious damage to business and environment, and in some worse cases, human loss. It has been estimated that urban flooding costs in Cairo in terms of property damage were 5.7 Millar Egyptian pound during the period from 2007 to 2012 [2], in addition immeasurable emotional disturbance to flood-affected people. Furthermore, the Egyptian Infrastructure is in very poor condition and need about 2.5 million $ per every year [3].Sewage rehabilitation plays an important role but is not easily processed due to uncertainty of occurrence of sewer pipe defects. Thus, worldwide engineers pay a greater attention to the proactive and preventive repair strategies than the traditional approach of regular sewer maintenance [4]. Lack of the deterioration models and sewer pipes crack prediction was the principle motivation for this study.

The primary aim of this study was to predict the deferent levels of sewer pipes cracks. The secondary aim of this study was to predict the sewer pipes cracks and the developments in these cracks during any period of time.

2. RELATED WORK
There were many studies and models on the prediction of sewer pipes cracks for the purpose of detecting cracks and preventing sewer pipes crashing . [5], described image analysis and pattern recognition techniques of sewer inspection, based on neural network analysis of digitized video images. The neural network analysis technique was found helpful in identifying four categories of sewer defects: cracks, joint displacements, reduction of cross-sectional area. [6] Developed an automated sewer inspection data interpretation system.

The other approach is to predict a sewer’s existing condition prior to its detailed inspection for selective, cost effective sewer inspection. [7] developed a method for predicting sewer pipes condition based on the knowledge of pipe material, length, diameter and other characteristics. However, it was concluded that the method could not evaluate sewer’s condition effectively.[8] developed a logistic regression model for condition evaluation of sewers. The model was developed through historical data based upon factors; such as, pipe age, diameter, material, waste type and depth. Another approach for condition assessment of large sewers was developed by assessing the impact of different factors; such as location, size, burial depth, functionality etc. in[9] . [10] developed a methodology of forecasting condition of sewers by using transition curves. These transition curves were developed through the historical condition assessment data. Sewers characteristics; such as, material, period of construction, location were used to define the existing condition of sewers for scheduling detailed inspection.[11] proposed a fuzzy set theory based approach for a pipe’s condition assessment. [12] used rule-based simulation methodology to predict condition rating of sewers. The model predicted the condition rating of pipe based on age, material and length of pipe. [13] developed an artificial neural network model for predicting the condition of sewers based on historical data. There is no clear conclusion regarding the quality of prediction that can be reached [14].

2.1 Markov model

Markov-chains are a stochastic process that describes the behavior of systems that pass through a finite or countable number of possible condition states. It is a random process characterized due to the key assumption that the prediction of a future condition only depends on the current condition and is independent of the sequences of events that preceded it. At each time step, the system may change its condition state from the current to another worse condition or remain in the same condition, according to a given probability.

2.2 Markov Model Prediction

Transition probabilities can be used to simulate the expected condition of the sewers in the future. The condition state vector p(t) indicates the probability distribution of condition states at any time t according to the calibrated survival functions (Figure 6). The probability vector p(t+1) at time t+1 can be obtained by multiplying the current condition state vector pT(t) by the transition matrix Q(t,t+1). More generally, to obtain the probability distribution at time t+s:

$$P^{T} = (t+s) = P^{T}(t)\prod_{i=1}^{s} Q(t, t+i) \qquad (1)$$

Table I. Comparison between the 8 previous models

model	Strong points	Weak points
Moselhi	1-Giving more details of cracks and joint 2-This model has been presented for automating the identification process of surface defects in underground water and sewer pipes	1-The disability to predict the developments of cracks 2-The security system in this model isn't clear 3-This model used black & white camera instead of color camera so the scanned image resolutions is weak 4-The data captured comes from video images because this model used CCTV(Closed circuit television) ,in video images A typical video image may consist of 512=512 pixels . 5-In this model one neuron would be needed for each single pixel in the image. This would require a huge number of neurons in the input layer that cannot be handled efficiently 6-The importance of time in this model wasn't found.
Ruwanpura	used rule based simulation Methodology to predict condition rating of sewers. The model predicted the condition rating of pipe based on age, material and length of pipe	1-The disability to predict the developments of cracks 2-The importance of time in this model wasn't found. 3-makes the task of planning, prioritizing and allocating funds a complex exercise
Markov	It's conceptual and computational simplicity.	1-The disability to predict the developments of cracks
Najafi	Using artificial neural network model for predicting the condition of sewers based on historical data.	1-The disability to predict the developments of cracks 2-The importance of time in this model wasn't found . 3-The way of obtaining historical data not clear
Baur	developed a methodology of forecasting condition of sewers by using transition curves	1-The disability to predict the developments of cracks 2-The importance of time in this model wasn't found . 3-Depends on historical condition assessment data only
Kulandaivel	The prediction depend on historical data only	1-The disability to predict the developments of cracks 2-The importance of time in this model wasn't found .

As shown in Table I ,the comparison between pervious 8 models including the strong and the weak points .The above mentioned approaches tend to predict existing condition of sewers for prioritizing detailed inspections, also these models hadn't The ability to predict the developments of cracks and the importance of time in these modes weren't find .

This paper proposes a model for predicting cracks in sewer pipes cracks for any period of time. In section II, the data set including sewer pipes image collection is described. Section III presents crack detection using canny algorithm while section IV presents our proposed model for crack detection for any period of time. Experimental work and results are presented in section V followed by a conclusion in section VI.

3. PROPOSED MODEL STEPS

3.1 Sewer pipes image collection

A commercially available SONY-DSC T5 digital camera of 5.1 mega pixels with optical zoom 3x has been used for data collection of 101 crack surface defects. Figure 1 shows one of these images. These images have been taken to Cairo sewer pipes network. MATLAB functions DILATE (), THRESH () and LAPLACIAN () were developed and applied to this image collection.

Fig 1: One of the 101 trail images

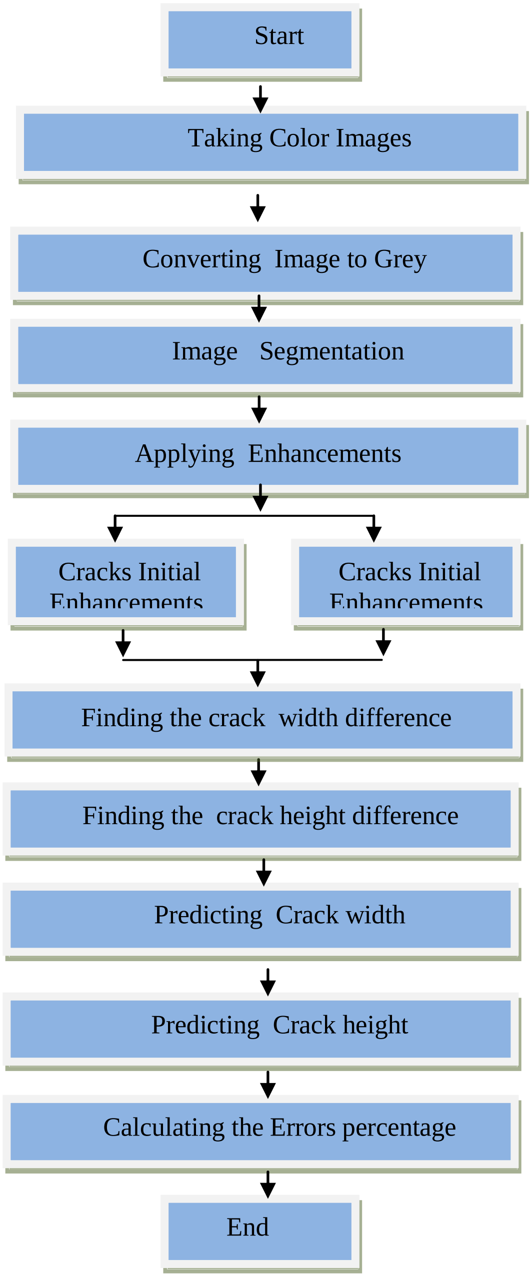


Fig 2: Proposed Model Steps

3.2 Canny Edge Detector

Segmentation of an image entails the division or separation of the image into regions of similar attribute. The most basic attribute for segmentation is image luminance amplitude for a monochrome image and color components for a color image. Image edges and texture are also useful attributes for segmentation [15]. Image segmentation techniques include thresholding methods, boundary/edge-based methods and region based methods. This section presents the steps needed to implement the canny edge detector for crack detection.

The first step is to filter out any noise in the original image before trying to locate and detect any edges. After smoothing the image and eliminating noise, the second step is to find the edge strength by taking the gradient of the image. The Sobel operator performs a 2-D spatial gradient measurement on an image. Then, the approximate absolute gradient magnitude (edge strength) at each point can be found. The Sobel operator uses a pair of 3x3 convolution masks Figure 3, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows). These masks are applied to every pixel in the image.

-1	0	+1
-2	0	+2
-1	0	+1

G_x

+1	+2	+1
0	0	0
-1	-2	-1

G_y

Fig 3:The 3x3 convolution masks used by the Sobel operator

The third step is to find the edge direction which is computed simply using the formula:-

$$\Theta = \tan^{-1} (G_y / G_x). \qquad (2)$$

Once the edge direction is known, the next step is to relate the edge direction to a direction that can be traced in an image. So if the pixels of a 5x5 image are aligned as follows:

x x x x x
x x x x x
x x a x x
x x x x x
x x x x x

$$P_2(T) = \sum_{z=T+1}^{L-1} h(z) = 1 - P_1(T) \qquad (3)$$

It can be observed by looking at pixel "a" that there are only four possible directions when describing the surrounding pixels – 0 degrees (in the horizontal direction), 45 degrees (along the positive diagonal), 90 degrees (in the vertical direction), or 135 degrees (along the negative diagonal). Now, the edge orientation has to be resolved into one of these four directions depending on which direction it is closest to (e.g. if the orientation angle is found to be 3 degrees, make it zero degrees).according to equation 3 .

3.3 Crack Detection

We propose a model to discover sewer pipes cracks. A series of steps have to be performed Figure 3.

3.3.1 Converting Colored Images to Grey

The proposed system has been used for binary (black and white) images and has been extended later to be used with grayscale images as well. The light and dark portions of an image can be reshaped or morphed in various ways under a control of a structuring element which can be considered as a parameter to morphological operation [16]. The MATLAB function im2bw () is used to convert a colored image to a binary image .

3.3.2 Image Segmentation

Segmentation of an image entails dividing or partitioning of an image into regions of similar attributes. The most basic attribute for segmentation is image luminance amplitude for a monochrome image and color components for a colored image. Image edges and texture are also useful attributes for segmentation [17].

Sets A and B in z (image) are defined to represent a grey-level image consisting of pixels p(x, y) and a structuring element Figure 4, respectively:

$$A=\{(x,y)|p(x,y)\} \qquad (4)$$

$$B=\{(x,y)|p(x,y)\} \qquad (5)$$

Converting scanned images into binary images for segmenting pipe defects by using a thresholding method and determining the optimal thresholds for the opening operated gray-level images by maximizing the following measure of class reparability [18].

$$D(T) = \frac{(P_1(T)P_1(T)[m_1(T)-m_2(T)]^2)}{P_1(T)_1^2(T)+P_2(T)_2^2(T)} \quad (6)$$

Where :-

$$P_1 = \sum_{z=0}^{T} h(z) \quad (7)$$

$$m_1(T) = \frac{1}{P_1(T)}\sum_{z=0}^{T} h(z) \quad (8)$$

$$m_2(T) = \frac{1}{P_2(T)}\sum_{z=T+1}^{L-1} zh(z) \quad (9)$$

$$\sigma_2(T) = \frac{1}{P_2(T)}\sum_{z=T+1}^{L-1}[z-m_2(T)]^2h(z) \quad (10)$$

Equations 6-10 apply segmentation in the original images . z is the grey-level of a pixel in the scanned image and ranges from 0 through L – 1, h(z) is the normalized grey-level histogram of the scanned image. By maximizing the criterion function in Equation 4-5, the means of the light and dark image regions can be separated as much as possible and the variances of the two image regions can be minimized.

3.3.3 Applying Initial Enhancements on Images

The contrast of the RGB pipe image has to be improved by enhancing the dark (crack) pixels relative to the background image. In order to perform crack enhancements, erosion and dilation operators are used. Erosion and dilation are two fundamental operators of digital image processing and whose implementations are of great value in the area of image analysis.

The dilation process is performed by laying the structuring element B on the image A and sliding it across the image .

The dilation of A by B, A $\oplus$ B, is the union of all pixels in A surrounded by the shape of B [19] and is defined as:

$$A \oplus B = \{a + b \ \ \forall\, a \in A \text{ and } b \in B\} \quad (11)$$

The dilation algorithm is applied as:

1. If the origin of the structuring element coincides with a ‘white’ pixel in the image, there is no change; move to the next pixel.

2. If the origin of the structuring element coincides with a ‘black’ in the image, make black all pixels from the image covered by the structuring element. Figure 4 shows the shape of the structure element.

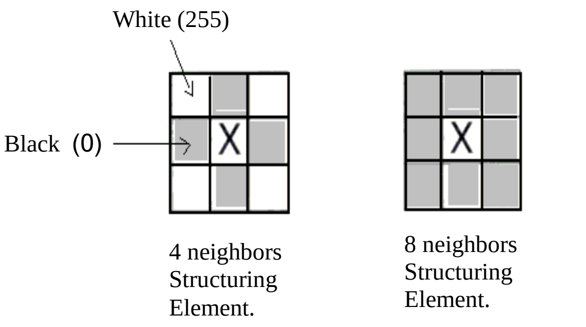


Fig 4: Typical shapes of the structuring elements (B)

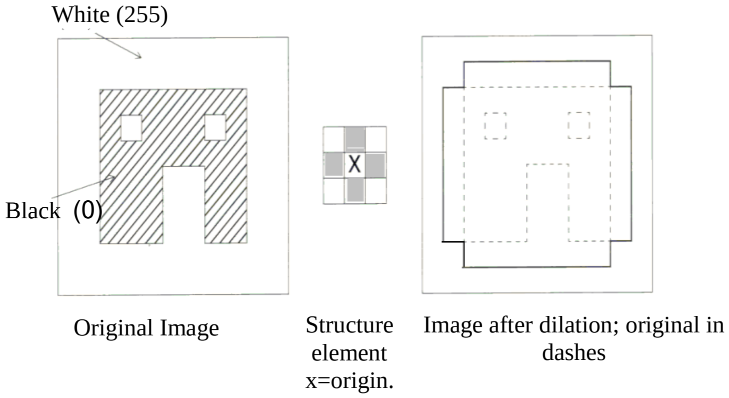


Fig 5: Illustration of the dilatation process

The example shown in Figure 5 shows that with a dilation operation, all the ‘black’ pixels in the original image will be retained, any boundaries will be expanded, and small holes will be filled.

The erosion process is similar to dilation, but we turn pixels to ‘white’, not ‘black’. As before, slide the structuring element across the image and then follow these steps:

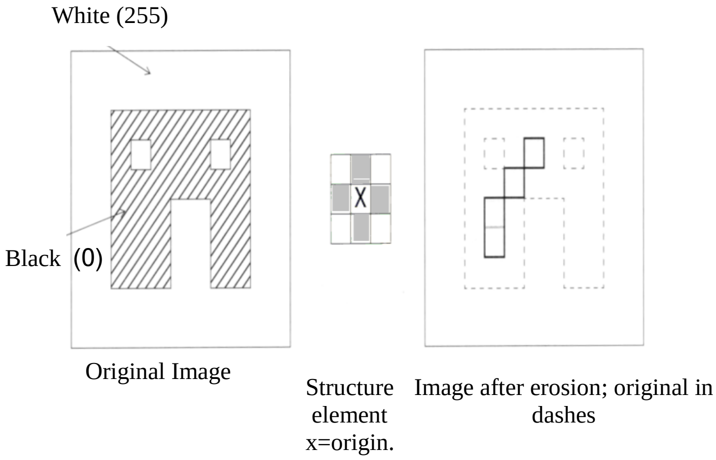


Fig 6: Illustration of the erosion process

1. If the origin of the structuring element coincides with a ‘white’ pixel in the image, there is no change; move to the next pixel.

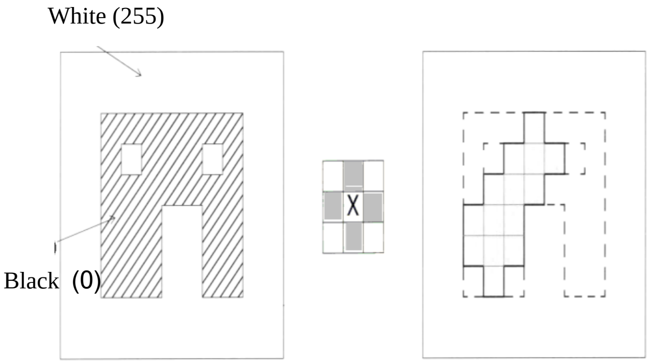
2. If the origin of the structuring element coincides with a ‘black’ pixel in the image, and at least one of the ‘black’ pixels in the structuring element falls over a white pixel in the image, then change the ‘black’ pixel in the image (corresponding to the position on which the center of the structuring element falls) from ‘black’ to a ‘white’.

Erosion of A by B, denoted as A Θ B, removes all pixels within a distance B from the edge of A (Figure 6) and is defined as:

$$A \,\Theta\, B=\{a|b+a \in A \text{ for every } b \in B\} \quad (12)$$

The opening operation is defined as:

$$A \circ B = (A \,\Theta\, B) \oplus B \quad (13)$$



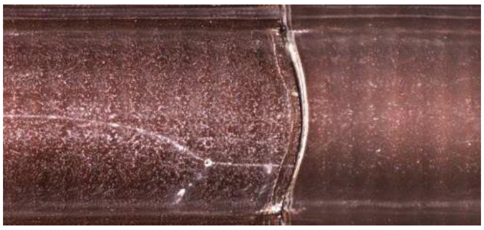
Original Image | Structure element x=origin. | Image after opening erosion followed dilation.

Fig 7: Illustration of the opening process

These two basic operations, dilation and erosion, can be combined into more complex sequences as shown in Figure 7. The most useful of these for morphological filtering are called opening and closing [19]. Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image.

The effect of opening operation is to remove image regions which are lightly relative to the structuring element while preserving image regions greater than structuring elements [16].

Converting scanned images into binary images for segmenting pipe defects by using a thresholding method and, determining the optimal thresholds for the opening operated gray-level images by maximizing the following measure of class separability [20].



(a)Original image with pipe crack

(b) Image after applying dilation with min=0 and max=255

Fig 8: Pipe crack image before and after dilation

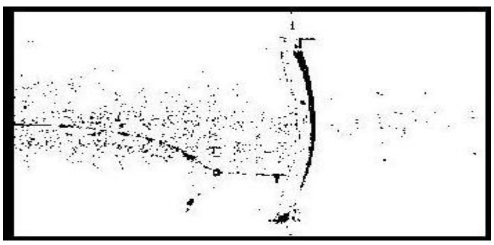


Fig 9: Applying filters to find cracks

3.3.4 Crack Enhancement

Before finally detecting the cracks, some enhancement steps are applied to the preprocessed image as shown in Figure 8 and Figure 9. The first enhancement operation on the image is applying a Laplacian filter. The Laplacian of an image f(x,y) denoted ∇^2 f(x, y) is defined as [19]:

$$\boldsymbol{\nabla^2 f(x,y)} = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \quad (14)$$

Commonly used digital approximations of the second derivatives are

$$\frac{\partial^2 f}{\partial x^2} = f(x+1,y) + f(x-1,y) + 2f(x,y) \quad (15)$$

and

$$\frac{\partial^2 f}{\partial y^2} = f(x,y+1) + f(x,y-1) + 2f(x,y) \quad (16)$$

From equations (14), (15) and (16), it is deduced that

$$\nabla^2 f = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) + 4f(x,y) \quad (17)$$

This expression can be implemented at all points (x, y) in an image by convolving the image with the following spatial mask:

$$\begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix}$$

An alternate definition of the digital second derivatives takes into account diagonal elements, and can be implemented using the mask:

$$\begin{matrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{matrix}$$

Both derivatives sometimes are defined with the signs opposite to those shown here, resulting in masks that are the negatives of the preceding two masks. Enhancement using the Laplacian is based on equation 18.

$$G(x,y) = f(x,y) + c[\nabla^2 f(x,y)] \quad (18)$$

Where $f(x,y)$ is the input image, $g(x,y)$ is the enhanced image, and c is 1 if the center coefficient of the mask is positive, or -1 if it is negative [20] because the Laplacian is a derivative operator, it sharpens the crack but drives constant areas to zero. Adding the original image back restores the gray-level color.

3.4 Crack prediction model

3.4.1 Prediction of crack width

Calculating crack width as shown in Equation 21.predicts the crack development for any period of time every period equals 4 (four) months .The starting measured crack width is the initial crack width for any crack measurements and the calculated cracks. p_1 Is a function includes the time calculations which divides into periods every period equal to four months.

3.4.2 Prediction of crack width

Equation 22 shows the developments of crack height during any period of time .Height factor T is used to cover the increasing in height crack than the width crack .This T is between .35 mm and .55 mm, if this factor is near to, 35 the error percentage will be small, the maximum value of this factor doesn't exceed .55 mm. In both calculating crack width and height the final value is a cumulative value of height and width during the certain period of time.

$$h_v = P_1\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{1}\right) * T, P_2\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{2}\right) * T, P_3\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{3}\right) * T, \ldots P_n\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{n-1}\right) * T \qquad (19)$$

3.4.3 Calculating the difference in crack width

Equation 20 shows the deference values between the measured crack width and the calculated crack width, this v can be calculated and predicted during any period of time, this period can take any positive value but in fact this period doesn't less one week.

$$w_v = P_1\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{1}\right), P_2\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{2}\right), P_3\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{3}\right), \ldots P_n\left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t}{n-1}\right) \qquad (20)$$

$$C_w = m_1(P_1 + w) + m_2(m_1 + p_2) + m_2(m_2 + p_3), + \cdots + m_n(m_{n-1} + p_n) \qquad (21)$$

3.4.4 Calculating the difference in crack height

Equations 21 Shows the deference values between the measured crack height and the calculated crack height, these values can be calculated and predicted during any period of time, this period can take any positive value but in fact this period doesn't less one week

$$C_h = n_1(D_1 + h) + n_2(n_1 + D_2) + n_2(n_2 + D_3), \ldots + n_n(n_{n-1} + D_n) \qquad (22)$$

Where:

$$D_1 = \left(\frac{t^3}{\sqrt{t}}\right)\left(\frac{t^3}{P^n}\right) * T \qquad (23)$$

w_v: The difference of crack width between the Measured and calculated width

C_h : The difference of crack width between the measured And calculated width

t :The time in months

p_n: The number of periods within one year

p :Period factor

m:The start width +the increase in width in the first period

C_w : The total width of crack during the period

C_h : The total height of crack during the period

T: Height factor (>=.35 ,<=.55)

Table 2 shows the difference between the actual value of width and the measured value of width also this table the difference between the actual value of height and the measured value of height .The development of both cracks width and height are remarked and calculated every period during one year ,here every period equal four months .

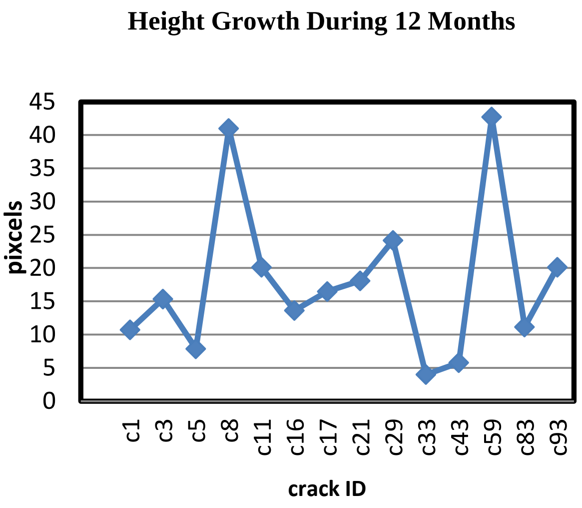


Fig 10: The development of cracks height during one year

Figure 10 show the development of cracks during 12 months, both c8 and c59 are the biggest crack height .Both c5 and c33 are the smallest crack height. Most cracks are in the middle of the chart 10.

The increasing of one crack width during one year in this case the year divides into four period every period equal to months ,in the first period the starting actual value of this crack width is 33.75 mm.

4. RESULTS

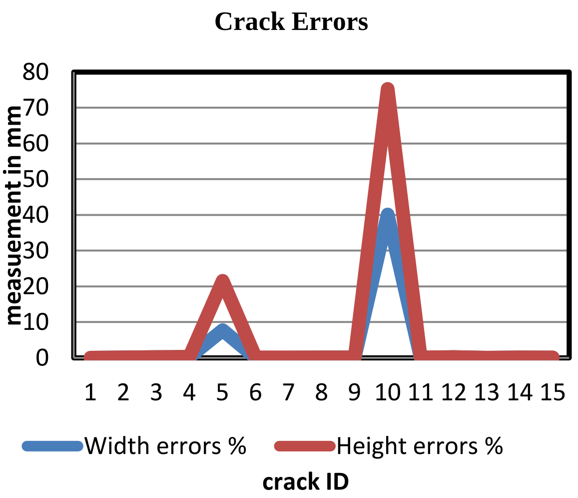
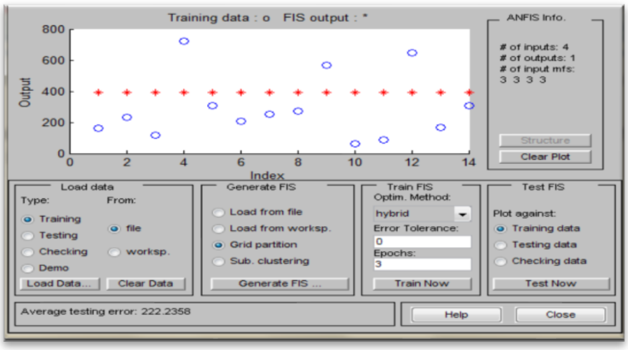


Fig 11: The error percentage Using Fuzzy logic

Fig 12: The errors of calculating crack width and height

- There are two cracks only have big values of crack width and height ,these cracks are c8 and c29 as shown in Figure 11.
- The error average percentage of crack width prediction is only **3.4865** and the error average percentage of crack height prediction is **3.5140** as shown in Table 3.
- The development of crack height is bigger than the development of crack width as shown in Table 3.



- The perdition accuracy of crack width is about 96 %and the prediction accuracy of crack height is about 95%.
- This model can predict the crack width and crack height for any period of time as shown in Equation 21 and Equation 22.
- In this model , the period of time takes any positive value so this model can predict the height of crack and the width of crack during time in the future.

The proposed model helps the operators to prevent sewer pipes crash and enables rehabilitation and replacement intervals in suitable. Fuzzy logic in MATLAB and Image J ver1.46r application are used for our implementation. The error percentage is calculated by comparing testing and training data as shown in Figure 15.

Table 2. Comparison between the proposed model and the 8 previous models

Table 2. Comparison between the 8 previous models

Items	Proposed model	Pervious 8 model
Accuracy of prediction	About 94%	About 30%
Number of Crack levels	many	1
Attributes included	Crack width, crack height, crack pixels	Focus on conditions and other materials only
Cost	Need very cheap tools	Need very expensive machines
Easiness	Very easy	Very difficult because of using complicated machine
Main technique	Taking many regular images	Used tools may miss defects hidden behind obstructions or under water
Time	Predicting both crack width and crack height for any period of time	The importance of time in these models wasn't clear .

As shown in Table 2, the proposed model has many advantages over the previous models. The accuracy of the proposed model is about 94% which is greater than the accuracy of the previous models. The proposed model has many crack levels according to the used periods but the other models have only one crack level. The proposed model focuses on the crack so it helps to predict what will happen to this crack in the future.

5. CONCLUSION

Crack detection techniques depend on the human eye. This paper presents an analytical model together with its implementation for the purpose of detecting cracks as well as predicting the crack width and crack height for any period of time. Using our model, very small cracks which can't be detected by the human eye can be detected and predicted in suitable time. The accuracy of both detection and prediction exceeds 94% which outperforms other approaches.

Table 3. Comparison between the 8 previous models

c_i	starting data		Actual data after 12 months		Calculated data after 12 months		**Width errors %**	**Height errors %**
	w_1	h_1	w_2	h_2	w_4	h_4		
c1	**34.41**	**152.08**	36.50	162.80	36.5205	162.8049	**0.0561644**	**0.0030**
c3	**28.03**	**217.67**	29.70	233.00	29.7522	233.0141	**0.1757576**	**0.0061**
c5	**15.20**	**111.56**	16.10	119.45	16.1349	119.4290	**0.2167702**	**0.0176**
c8	**33.57**	**581.53**	**38.60**	**722.49**	**35.6322**	**622.5310**	**7.6886010**	**13.8353**
c11	**21.87**	**285.52**	23.20	305.68	23.2099	305.6512	**0.0426724**	**0.0094**
c16	**17.33**	**193.33**	18.40	206.90	18.3967	206.9644	**0.0179348**	**0.0311**
c17	**17.79**	**233.77**	18.90	250.25	18.8806	250.2535	**0.1026455**	**0.0014**
c21	**17.08**	**256.55**	18.10	274.63	18.1228	274.6333	**0.1259669**	**0.0012**
c29	**24.23**	**342.77**	**42.93**	**566.20**	**25.7211**	**366.9324**	**40.0859539**	**35.1939**
c33	**11.54**	**56.73**	12.25	60.70	12.2513	60.7342	**0.0106122**	**0.0563**
c43	**9.44**	**82.01**	10.00	87.80	10.0140	87.7944	**0.1400000**	**0.0064**
c59	**24.04**	**606.01**	25.50	648.75	25.5110	648.7391	**0.0431373**	**0.0017**
c83	**34.41**	**158.08**	36.50	169.20	36.5227	169.2279	**0.0621918**	**0.0165**
c93	**21.87**	**285.52**	23.20	305.70	23.2099	305.6512	**0.0426724**	**0.0160**
The error average % of both width & height crack							**3.4865**	**3.5140**

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