Pothole Detection with Image Processing and Spectral Clustering

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Abstract: Pothole detection is one of the important tasks for the proper planning of repairs and rehabilitation of the asphalt-surfaced pavements. Pothole repair is necessary in those situations where potholes compromise safety and pavement ride-ability. Existing methods for detection and estimation of potholes usually use sophisticated equipment and impose computationally intensive tasks. In this paper, we present a new unsupervised vision-based method, which does not require expensive equipment, additional filtering and training phase. Our method deploys image processing and spectral clustering for identification and rough estimation of potholes. Spectral clustering is used for identification of regions with histogram-based data from gray-scaled image. Based on these results, we identify potholes and estimate their surface. Method is tested on images with different pothole shapes and the results show that this method estimates potholes with reasonable accuracy.

Key–Words: Pothole detection, Unsupervised method, Spectral clustering, Image processing, Image segmentation, Vision-based approach

1 Introduction

Asphalt-surfaced pavements are subjected to a broad spectrum of traffic levels, from two-lane rural routes to multi-lane interstate highways. They age and deteriorate, thus they require corrective measures to restore safety and ride-ability [1]. The most common forms of distress on asphalt-surfaced pavements are *potholes* - small, bowl-shaped depressions in the pavement surface. Pothole repair is necessary in those situations where potholes compromise safety and pavement ride-ability.

Pothole detection and estimation is one of the important tasks for the proper planning of reparation and rehabilitation of the asphalt-surfaced pavement. Road maintaining companies need many technicians for manual collection of data, and many working hours for rough estimation of damage on the road. There are many factors which influence decisions for pothole patching, such as the level of traffic, the time until scheduled rehabilitation or overlay, the availability of personnel, equipment, and materials, and the tolerance of the traveling public. The cost-effectiveness of the overall patching operation is affected by material, labor, and equipment costs. The key of decision making for future reconstruction is estimation of damage from collected information.

In current practice, sophisticated digital inspection vehicles are used to collect pavement images and video data, but the estimation of damage is reviewed manually by technicians. Thus, it is a time-consuming and costly task. Since it depends on worker's precision and experience, it is usually more subjective than objective. Existing applications usually need sophisticated equipment which is very expensive, and usually requires special maintenance [2].

There are three approaches for pothole detection which are based on 3D reconstruction [8], vibration [7] and vision-based analysis [2, 3]. The first approach requires high cost laser scanners, while second approach is not reliable when a surface vibrates, such as bridge expansion joints. Vision-based approach relies on image processing analysis. Existing methods are based on texture extraction and comparison, which requires additional filtering methods and a set of training data. Essentially, these are supervised methods, which suffer from a problem of overfitting, thus the characteristics of training set are memorized instead of capturing the desired pattern.

In this paper, we propose a new unsupervised method, which is based on image analysis and spectral clustering. It is vision-based method, which does not require additional filtering and training phase. Data is collected by using in-expensive and omnipresent equipment mounted on passenger vehicles and off the shelf digital cameras for video acquisition. The first phase is detection of frames with defects, which are then analyzed with our method. We use spectral clustering to identify regions by using histogram-based data from gray-scaled image. Based on results, we identify potholes and estimate its surface. Our method is suitable for rough estimation of potholes, and it is cost effective because it uses in-expensive equipment. The results show that this method detected potholes with reasonable accuracy.

The paper is organized as follows: related work on identification and detection on pothole using image processing is briefly reviewed in section 2. In section 3, we propose a new method for pothole identification and estimation. Experimen-

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tal results are presented in section 4, and in section 5 we conclude the paper with some remarks.

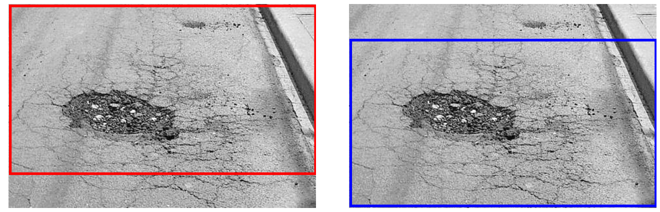
2 Related Work

There are three approaches for pothole detection based on: 3D reconstruction, vibration and vision analysis. 3D reconstruction of the pavement surface can be acquired by laser scanners and stereo-vision algorithms using a pair of video cameras. These methods visualize 3D pavement surface data by using sophisticated, high cost equipment, and exhibit high computational cost [8]. Vibration-based approach uses accelerometers [9] to assess pavement condition based on mechanical responses of the vehicle which carries equipment. The equipment for this approach is very cost-effective, but it cannot be used at bridge expansion joints and cannot detect pothole in the center of a lane as reported in Eriksson et al. [7].

There is a relatively little work on vision-based approaches. In [10], Karuppuswamy proposed new method based on integrating vision and motion system for detection of simulated potholes. However, its disadvantages are that it cannot detect potholes smaller than 2 feet in diameter, and a pothole has to be white in color. In [3], Koch et al. proposed a novel supervised approach for automated pothole detection based on asphalt pavement surface images. This approach is based on pothole texture extraction and comparison, where the surface texture inside a pothole candidate has to be described and compared with the texture of the surrounding region. This implies existence of a number of pothole texture samples from which the system is trained. System can identify a pothole based on these training results. Additionally, four spot filters are required to be applied to original gray-level image in order to emphasize structural texture characteristics.

3 Methodology

The condition of pavement assessment is evaluated by collecting appropriate data, then identifying distressed regions and lastly estimating potholes surface. Traditionally, the first phase is automatically collected by using sophisticated digital inspection vehicles [3] with sensors such as laser scanners, optical sensors, ultra sonic sensors and accelerometers which contribute to more accurate pavement assessment. Even though these methods are very accurate, the number of such vehicles is limited due to the very high cost of equipment. In this paper, we investigate possibility of using inexpensive and omnipresent equipment by employing regular passenger vehicles and off the shelf digital cameras for video acquisition. Currently, identification of distress region is performed manually by selecting video frames with possible potholes. In the next sections, we propose a new unsupervised method by using image processing and spectral clustering for identification and estimation of potholes on asphalt-surfaced pavements.



(a) The image is cropped for δ rows from bottom (marked red).

(b) The image is cropped for δ rows from top (marked blue).

Figure 1: The process of forming two cropped images from the original image.

3.1 Image segmentation

Image segmentation detects relevant information from digital images, and it is the first step of image analysis and pattern recognition. There are several methods to perform image segmentation including thresholding, clustering, transform and texture methods [4]. The simplest approach to segment an image is histogram-based thresholding. It assumes that an image is composed of different color or gray regions. The first step is conversion of an image from RGB values into gray scale. The pixels are partitioned depending on their intensity values and results should reveal two peaks, corresponding to the signal from the background and foreground (objects). Histogram-based thresholding consists of setting intensity values - threshold (T), which separates background from the object(s) of interest. Based on the value on T, the image is converted from a histogram $h(x, y)$ into a binary image $g(x, y)$ using Eq. 1.

$$g(x,y) = \begin{cases} 1, & \text{if } h(x,y) \leq T \\ 0, & \text{if } h(x,y) > T \end{cases} \quad (1)$$

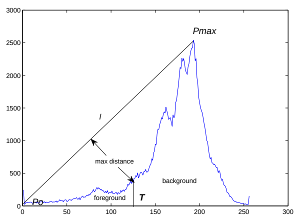
The result of histogram-based thresholding depends on a degree of intensity separation between the two peaks in the image. In [3], Koch et. al proposed histogram shape-based thresholding algorithm, which is based on the triangle algorithm presented in [12]. However, in some cases it is difficult to distinguish objects from the background because we need additional filters to remove noise from the image.

In our case, we use Otsu's image thresholding method [4, 5] to determine T, and then we form two new cropped images based on T and image pixels as presented in Eq. 2:

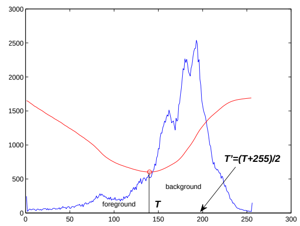
$$\delta = |T - \sum_{i=1}^{x} \sum_{j=1}^{y} (p_{ij})/xy| \times 2 \quad (2)$$

where T is threshold, x the number of rows, y the number of columns in the image, and p the value of the pixel of the specified position. In case when the δ less then 10, we change its value to 16 for cropped images. The process of forming two cropped images is presented in Fig. 1.

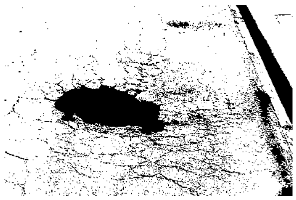
The resulting image after image segmentation with threshold T is illustrated in Fig. 2c, which is based on his-



(a) Triangle based thresholding.



(b) Otsu based thresholding.



(c) The result of binary image calculated with threshold T.

(d) The result of binary image with threshold T'.

Figure 2: Two different methods image segmentation for the pothole image.

togram in Fig. 2a. During this transformation small linear-shaped regions are removed using technique of filling pixels with the same values of surrounding pixels from the environment. For our case, we calculated the binary image $g^{'}(x, y)$ using Eq. 3, and the resulting image is illustrated in Fig. 2d.

$$g^{'}(x,y) = \begin{cases} 1, & \text{if } ci_1(x,y) - ci_2(x,y) \geq \frac{T^{'}}{4}, \\ 0, & \text{if } ci_1(x,y) - ci_2(x,y) < \frac{T^{'}}{4}. \end{cases} \quad (3)$$

Threshold $T^{'}$ is calculated with $\frac{T+255}{2}$, and ci_1 and ci_2 are cropped images.

3.2 Shape extraction

After image segmentation, we removed all linear shapes, and regions and shapes smaller than δ from the image. Measure for removing all these linear regions is defined by their eccentricity ϵ which is a relative parameter [13]. All shapes which are connected to the image boundary are also removed and the result of these operations is illustrated in Fig. 3.

Recently, spectral clustering [14] became one of the most popular clustering algorithms. Traditional clustering algorithms, such as the k-means algorithm, are usually not good enough for clustering data into predefined number of clusters. These algorithms use only simple metrics like Euclidean distance for calculating distances between points in a dataset and then make clusters by distance values (max or min).

There are many similar spectral clustering algorithms, but in this paper we used the most commonly used normalized spectral clustering algorithm according to Ng et.al [15] and [17]. The basic technique of the spectral clustering is to perform dimensionality reduction before clustering in fewer dimensions. As input in the spectral clustering we used affinity matrix $S = s_{(ij)}, i, j = 1, 2, .., n$ [14, 15], which

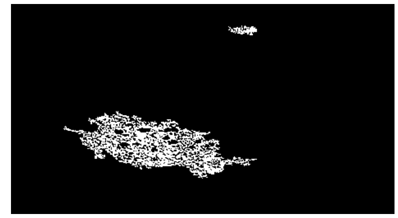


Figure 3: The resulting intermediate image with removed linear shapes, shapes smaller than δ and shapes which are connected to the image boundary.

contains relative similarity for each pair of n points in the dataset. This affinity matrix [6] is typically defined as $e^{\frac{-d^2}{\sigma^2}}$, in a way similar to the Gaussian kernel based on inter-point euclidean distance, where d is Euclidean distance between points and σ is a scale factor.

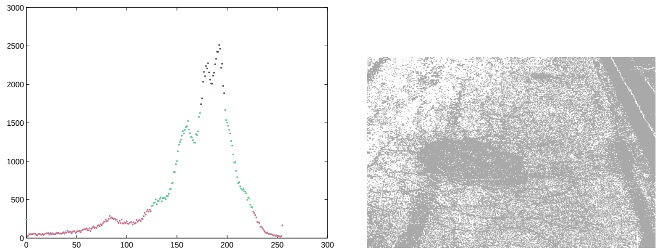
The basic steps of this algorithm are presented below:

- input: number k of clusters which need to construct
- for a given dataset of n points $X = x_1, ..., x_n \in R^l$ form the affinity matrix $S \in R^{n \times n}$ which is defined by $s_{ij} = e^{\frac{-d^2(x_i, x_j)}{\sigma^2}}, i, j = 1, 2, ..., n$, where $d(x_i, x_j)$ is some distance function (e.g. Euclidean) between points x_i and x_j
- compute degree matrix $D = diag(d_i)$ where $d_i = \sum_{j=1}^{n} s_{ij}$
- compute the normalized Laplacian matrix $L = D^{\frac{-1}{2}} \times L \times D^{\frac{1}{2}}$, where L is Laplacian matrix defined as $L = D - S$
- perform the eigen value decomposition by equation $L \times \upsilon = \lambda \times \upsilon$, where $\upsilon \in R^{n \times n}$ matrix of eigen vectors and $\lambda \in R^{n \times n}$ is matrix of eigen values
- form matrix $U \in R^{n \times k}$ from matrix υ, $u_{ij} = \upsilon_{im}$ where $i = 1, 2, ..., n; j = 1, 2, ..., k$ and m is k largest eigen vectors which are selected as the last k columns from matrix υ
- construct the normalized matrix Y from the obtained matrix U $y_{ij} = \frac{u_{ij}}{(\sum_{l=1}^{k} u_{il}^2)^{\frac{1}{2}}}$, where $i = 1, 2, ..., n; j, l = 1, 2, ..., k$
- clustering n points $y_i \in R^k, i = 1, 2, ..., n$ with K-means algorithm into $C_1, C_2, ..., C_k$ clusters

We used spectral clustering algorithm to extract shape regions in the gray-scaled image. For our case, we found that the affinity matrix S given by equation Eq. 4 gives the good results for image histogram values $h \in Z^{256 \times 2}$.

$$s_{ij} = e^{\frac{-d(h_i - h_j)}{2\sigma^2}} \quad (4)$$

There are different ways for selecting possible value of scale factor σ [15, 14, 6]. Some of them provide an intuitive



(a) Clustered histogram data (b) Resulting clustered image

Figure 4: Extraction of clustering results on pothole asphalt-surfaced pavement.

way for manual selection of possible values for σ, others select automatically by using more iterations of clustering algorithm for predefined set of σ values and try to select the one which provides the best clusters.

We calculated the scale factor σ from image histogram values h as illustrated in Eq. 5.

$$\sigma = (\sum_{k=1}^{2} \frac{\frac{1}{255}\sum_{i=1}^{256}(h_{ik} - \frac{1}{256}\sum_{j=1}^{256} h_{jk})^2}{(\frac{1}{255}\sum_{i=1}^{256}(h_{ik} - \frac{1}{256}\sum_{j=1}^{256} h_{jk})^2)^{\frac{1}{2}}})^{\frac{1}{2}} \quad (5)$$

The number of clusters we calculated using eigenvalues λ, limit η (Eq. 6) and Algorithm 1.

$$\eta = (\frac{1}{n-1}\sum_{i=1}^{n}(\lambda_{ii} - \frac{1}{n}\sum_{j=1}^{n}\lambda_{jj})^2)^{\frac{1}{2}} \quad (6)$$

Algorithm 1 Finding number of clusters

Require: η - Eq. 6; λ - eigenvalues

for $i \leq n; i \leftarrow i + 1$ **do** ▷ n is the number of eigenvalues points
  if $\lambda_{ii} > \eta$ **then**
    $k \leftarrow k + 1$
  end if
end for
return (k) ▷ k is the number of clusters

Clustered histogram data and extraction of clustering results on pothole image are illustrated in Fig. 4. There are only three clusters as can be seen from Fig. 4a. After applying clustering result on the image (using only three colors in our case), it is noticeable that one color has more density in the pothole region than others (Fig. 4b).

3.3 Identification and extraction of potholes

Steps used for identification and area extraction of potholes are illustrated in Fig. 5. Steps 1-4 in Fig. 5 are explained in sections Image segmentation and Shape extraction.

After extraction of clustering results (Step 5. in Fig. 5), the next step is selection of seeds (Step 6). This will mark

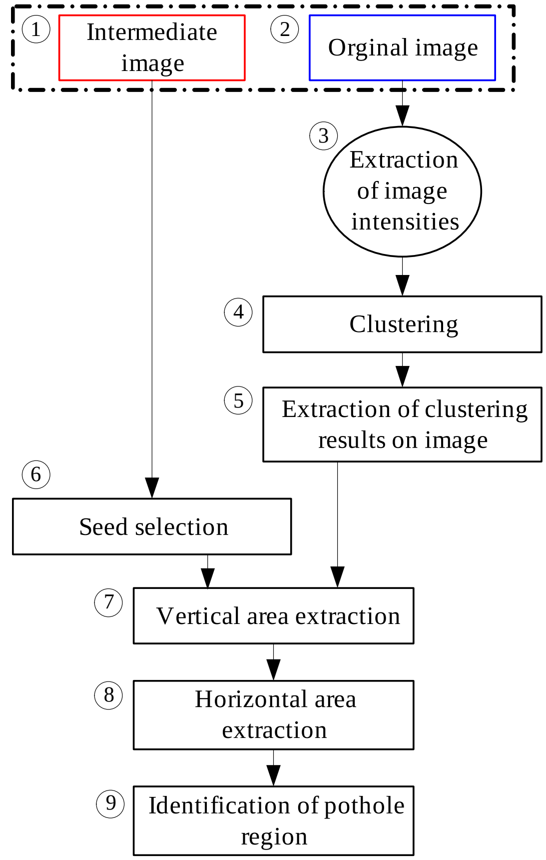


Figure 5: Steps for identification and extraction of potholes on asphalt-surfaced pavement.

the area for identification of pothole region. The selection of seeds depends of preciseness which we want to accomplish. If we decide to use greater number of seeds (or whole intermediate image area), the calculation of pothole area will be very time consuming. In our case, the better way is to select only a few seeds with good distribution on the intermediate image space. If we try to select seeds with good distribution, then this operation will be time consuming, which is not desired. Thus, we decided to select every 50^{th} point which will provide good results and fast execution (Algorithm 2).

The next step is vertical area extraction in the clustered image (Step 7). In this step, we first find the top vertical point for each seed, which has the same pixel value as the given seed. Also, all connecting points need to have the same pixel value. The same procedure applies for the bottom vertical point. After this operation we have vertically defined regions for a pothole.

Previous vertical operation is used as the basic for horizontal pothole extraction (Step 8). The initial seeds are not enough to completely identify a pothole. Thus, for each seed point all vertical connected points between the top and the bottom point are used as new seeds for horizontal extraction. In this step, we first find the farthest left point for each seed with the same pixel value as the given seed. Also, all horizon-

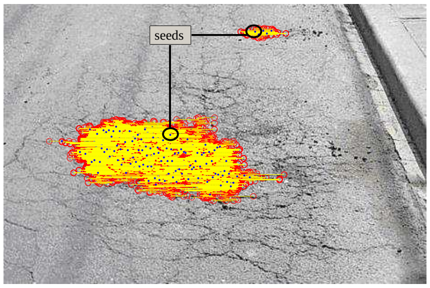


Figure 6: Pothole identification with vertical and horizontal extraction.

tal connecting points need to have the same pixel value. The same procedure applies for the farthest right point. After this operation, we defined horizontal regions for each seed point by using vertical area extraction.

Algorithm 2 Seed selection from intermediate image for clustered image

Require: $iImage$ - intermediate image; $cImage$ - clustered image

$(rows, columns) \leftarrow$ find all points where the pixel value is 1
for $i \leq$ size of number columns of iImage; $i \leftarrow i + 50$ **do**
  $k \leftarrow k + 1$ ▷ increment k for every cycle i
  $row \leftarrow rows(i)$ ▷ selection i^{th} row
  $col \leftarrow columns(i)$ ▷ selection i^{th} column
  $seedPoints(k) \leftarrow (row, col)$ ▷ k^{th} seed point
  $colors(k) \leftarrow cImage(row, col)$ ▷ selection k^{th} color
end for
return $(seedPoints; colors)$

The process of pothole identification (Step 9) is completed by plotting vertical and horizontal lines between points which provide means to perform extraction of pothole surface (Fig. 6). In the figure, two identified and extracted potholes on asphalt-surfaced pavement can be seen. Blue points in the extracted region represent seeds. These are the initial seeds which we found in intermediate image as was presented in Algorithm 2.

4 Implementation and Results

4.1 Implementation

Our method has been implemented in MATLAB version 7.11.0 (R2010b) with Image Processing Toolbox. The image processing was performed on Intel Core2 1.80 GHz CPU with 4GB of RAM.

The effectiveness of our method has been verified on a data collection selected from Google image collection. This approach allows convenient verification and comparison with similar methods.

4.2 Results

For rough estimation of potholes we used extracted areas as explained in section identification and extraction of potholes. The first step is to form the group from extracted areas. Every extracted area which has distance less than 5δ from other areas is included in the group. After that, we formed a rectangle which contains previously created group. The rectangle is formed in the similar way as the process of extraction areas of a pothole. We first find the top point in the group, and after that the farthest left point. From these points we formed a new point (top-left point) which have the same value of x coordinate as the farthest left point and y value as the coordinate of the top point. In the same way we formed a bottom-right point. We assume that camera captures surface area of about $5m^2$. The surface of a pothole is estimated as surface of rectangle through these two points.

The proposed method was tested on 50 different pothole images which include: 15 images with one pothole, 10 with multiple potholes, 10 with cracks and a pothole, 5 with repaired patches and the rest with no defect areas. Some results are presented in Fig. 7. Images with potholes are illustrated in Fig. 7 (a, e and i). Intermediate images from which we selected seeds are illustrated in Fig. 7 (b, f and j). Clustered pothole images are illustrated in Fig. 7 (c, g and k) and finally the results of pothole estimation are presented in Fig. 7 (d, h and f).

Based on these tests, we manually calculated accuracy of our method. The accuracy for the estimation of a pothole surface area is about 81%. We think that this information can be used for rough estimation for planning of repairs and rehabilitation of the asphalt-surfaced pavements.

5 Conclusion

In this paper we proposed a new unsupervised method based on image processing and spectral clustering. Spectral clustering is a simple method for finding structure in data, which uses spectral properties of an associated pairwise similarity matrix. The first phase is detection of frames with defects, which are then analyzed with our method. We use spectral clustering to identify regions by using histogram-based data from grayscaled image. Data is collected by using in-expensive and omnipresent equipment mounted on passenger vehicles and off the shelf digital cameras for video acquisition.

The proposed method was tested on 50 different pothole images and the detection accuracy has been calculated manually. On a given set of data, our method identified all potholes and the surface estimation was 81% accurate. Thus, it is suitable for rough estimation of potholes, and it is cost effective because it uses in-expensive equipment. The results show that this method detected potholes with reasonable accuracy. Future work will focus on estimation of potholes when the road has several cracks.

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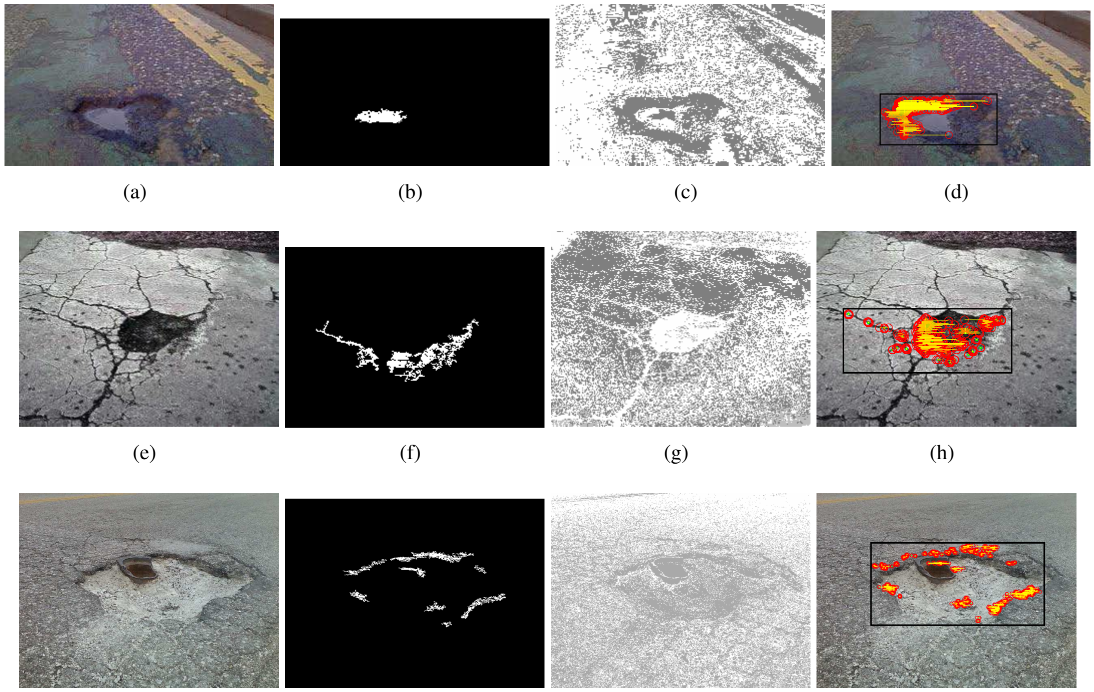

(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k) (l)

Figure 7: Results of pothole estimation on asphalt-surfaced pavement are presented in d, h, and l, where original pothole images are a, e, i; intermediate images: b, f, j and clustered images: c, g, k.

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