Research on Animal Feed and Animal Waste Detection based on Computer Vision

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***Abstract*—This paper presents algorithms to detect animal feed and animal waste for farming management. For the animal feed detection, the algorithms use color and Canny's edge feature to detect animal feed and obtain the animal feed detection area by morphological processes. For the animal waste detection, the contaminated area is calculated by using median filter together with Hough's straight line transformation.**

I. Introduction

As the development of farming, farming management becomes more and more automatic. Supervision by computer vision has many advantages: automatic supervision is cheap, efficient, accurate and easy to control. It provides supports for farming management and improves the productivity .

The animal feed detection is to detect the available animal feed in the detection area and the animal waste detection is to detect the area of contamination by animal waste in the sewers. Color features [1][2][3][4], edge features [5][6][7][8] and morphological processes are used to detect the animal feed. Median filter and Hough's transformation are used to detect the area of sewers that is covered by animal waste

II. Animal feed detection

Images are captured by cameras and ready for analysis. An example of a animal feed image is shown in Figure 1.

Figure 1: Animal feed input image

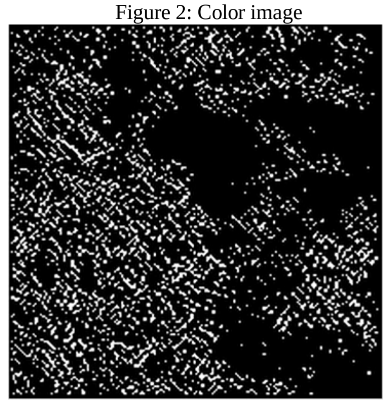
A. Color features

The animal feed in the image is mainly cured hay, which is grass yellow. The animal feed is placed on the ground, which is normally white in the image. Therefore, the animal feed detection area can be extracted by the color difference. Normal grass has excess green color and special color [1] in the image. It is called excess green effect (2G-R-B). The animal feed has the same features but with excess yellow color. It has less blue value (B) and closer red (R) and green (G) values. The animal feed has higher saturation value in soft light, which reduces the difficulty of the detection. Therefore, the animal feed can be detected by R>B, G>B and the following conditions:

` $$\begin{cases} B > \frac{R+G}{2} * 0.5 \\ B < \frac{R+G}{2} * 0.9 \\ G - R < 20 \\ R - G < 20 \end{cases} \quad (1)$$

The animal feed has pixels in yellow or dark yellow. In different lighting conditions, most of them can be detected easily. Figure 2 shows a detection result:

Figure 2: Color image



B. Canny's edge detection

The animal feed is dark black in weak light and has similar color to the ground in strong light. Also, it has obvious edge features in strong light. The ground is much smoother compared to the animal feed. Therefore, edge feature can be used to detect the animal feed as well. John.F Canny suggested three optimal criteria to edge detection in 1986 [9] . In order to obtain most the edge features of the animal feed, filtering process is not needed.

Canny's edge detection uses first-order derivative to calculate the magnitude and direction of each 2×2 pixels. The magnitude and direction can be expressed as:

$$M[x,y] = \sqrt{G_x(x,y)^2 + G_y(x,y)^2}$$

$$\theta[x,y] = \tan^{-1}\left(G_x(x,y)/G_y(x,y)\right) \quad (2)$$

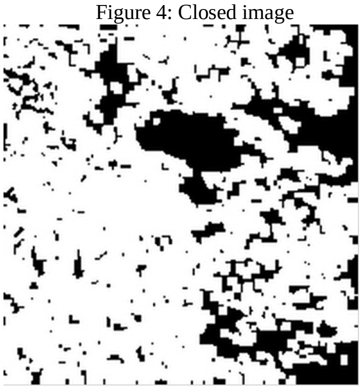
Then upper and lower thresholds are applied and discontinued edges are connected. Figure 3 shows an example of the edge feature. Finally, the edge feature and color feature are combined to detect the animal feed.

Figure 3: Edge image

C. Morphological processes

The color feature cannot combine with the edge feature because they are points and lines. Morphological processes are needed to transform the points and lines into contours. Morphological processes use a 3×3 operator to close the images twice. However, the noise pixels in the image are expanded too. An example result is shown in Figure 4.

Figure 4: Closed image

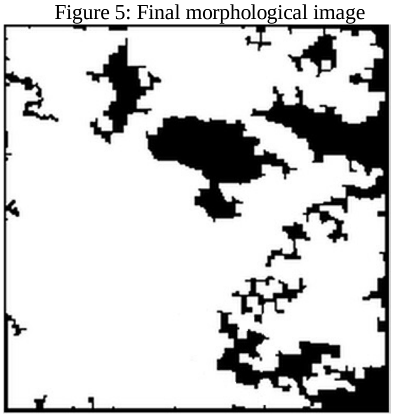


The closed image is then opened by a 10×10 operator to remove the noise pixels. After that the image is opened again to further reduce the expanded area. Finally the color feature and the edge feature are combined.

$$D_{(x,y)} = S1_{(x,y)} + S2_{(x,y)} \quad (3)$$

The final result is shown in figure 5.

Figure 5: Final morphological image



III. ANIMAL WASTE DETECTION

The cameras for the animal waste detection are installed in the stables. The system detects the area that covered by animal waste by detecting whether the anti-slip lines are covered. An example input image is shown as figure 6.

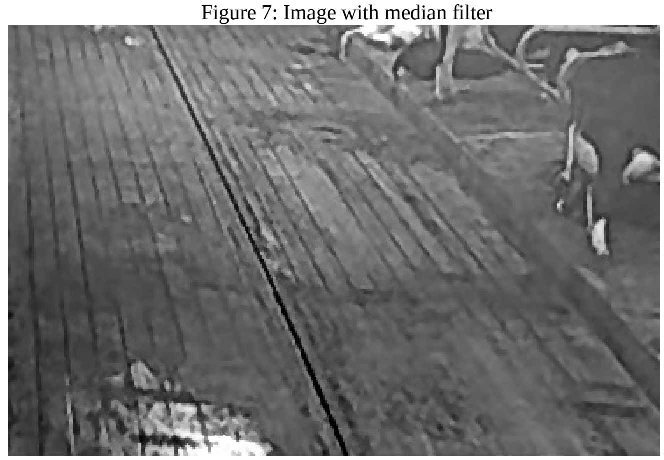
Figure 6: Animal waste input image

A. Median filter

Median filter is a non-linear filter. it is commonly used in image processing. Maximum and minimum values are not filtered in the process, so that median filter will not be affected by noises. Also, the impulse noise [9] in the image is smoothed without losing other edge details.

Most noises in the image are removed by the median filter so that the anti-slip lines are obvious in the image. The filter output $g(x,y)=med\{ f(x-k, y-l), (k,l \in \omega) \}$, $\theta[x,y] = \tan^{-1}(G_x(x,y)/G_y(x,y))$ where $f(x,y)$ and $g(x,y)$ are the original and filtered image respectively, ω is a 2-dimensions 3×3 template. This makes the following line detection works more effeciently on the filtered image. An example result from the median filter is shown in figure 7.

Figure 7: Image with median filter



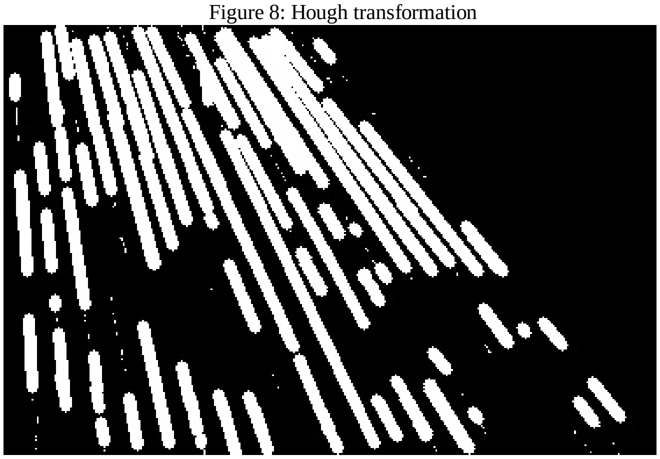
B. Hough's line detection

Hough's transformation is commonly used to connect discontinuous edges into a closed edge. It can also detect objects with known shapes. Moreover, noises and discontinuous distance have small effect on Hough's transformation. Both image space and parameter space are transformed to detect straight line:

$$\rho = x \cos \theta + y \sin \theta \quad (4)$$

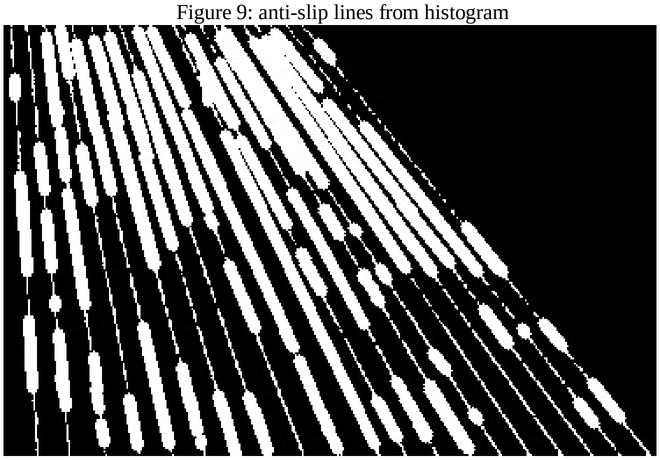
Lines are detected from the edge image. A line can be represent by $L(\rho,\theta)$ (ρ,θ) with end points (x_1, y_1) and (x_2, y_2) $(x1, y1)$ and $(x2, y2)$. The lines L_i are shown as thick lines in figure 8.

Figure 8: Hough transformation



The anti-slip lines that cannot be detected by Hough's transformation are regarded as lines covered by animal waste. The length ratio between the non-detected anti-slip lines and the detected lines is the area percentage of the animal waste. Figure 9 shows the detected lines and non-detected lines:

Figure 9: anti-slip lines from histogram



All the lines can be represented by L_1, L_2, L_3, $\cdots L_n$. The total length of all the lines is then $L= L_1+L_2+L_3+...+L_n$. All the detected lines are l_1, l_2, l_3, $\cdots l_m$, where $l_m \rightarrow \{(x_1,y_1),(x_2,y_2)\}$. The length of each detect lines can be calculated as $l_m= \sqrt{((x_1-x_2)^2+(y_1-y_2)^2)}$. Therefore, the total length of detected lines is $l= l_1+l_2+l_3+\ldots+l_m$. Finally, the area ratio that covered by animal waste is:

$$q=l / L \quad (5)$$

This ratio represents the contamination area ratio in the sewer. Also, the detection area can be set manually.

IV. Conclusion

This paper presents algorithms to detect feed and sewage for farming management. The animal feed is detected by color and edge features, together with morphological processes. It has better performance on concrete ground. The sewage detection algorithm detects the anti-slip lines to calculate the animal waste by median filter and Hough's transformation. These algorithms greatly promote the development of farming. Special conditions such as when the camera is too close to the animal feed or animals walk on the anti-slip lines may affect the performance. More methods are needed to overcome these problems to increase the true positive detection rate.

V. ACKNOWLEDGMENT

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VI. References

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