Machine Vision Guided Cleaning For Autonomous Pig Sty Cleaning

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Abstract

Cleaning of pig houses is a harsh labour intensive task and it can give respiratory problems. Existing robot cleaners are preprogramed and unselective in their application of water which makes them capable of cleaning only 60-85%. We propose a vision algorithm for a robot that can be used for variable rate application of controlled bursts of cleaning with the ability to align itself and segment the different types of surfaces, and would be easily employed in other domains. It is demonstrated on real farm images from an actual manual cleaning process and that it has the potential to clean until it is done while preserving water.

Key words: machine vision autonomous cleaning pigsty.

1. Introduction

It seems that there would be a pronounced utility of being able to perform automatic cleanliness inspection in relation to many types of cleaning tasks. This would be useful to integrate into robotic solutions, but also into consumer products, and industrial environments where cleanliness can be crucial, such as in the food or pharmaceutical industry. One consumer product example is dishwashers that are known to exploit combinations of optical and electrical parameters to assess the cleanliness of rinse water. Optically the turbidity of the water and electrically the resistivity of the water is assessed.

When it comes to agricultural environments references seems to be scarce. For pig sties in particular it seem attractive to explore the utility of using remote sensing principles, however only one group working on an optical system to assess pigsty cleanliness was found (Braithwaite et al. 2005). In this study the focus was very much on identifying spectral characteristics of cleanliness related to the various materials typically utilized in the pig sty, such as concrete, metal bars an plates of plastic-type materials.

Cleaning of pig houses is a harsh labour intensive task that makes it hard for farmers to keep their assistants unless they have an automatic robot cleaner (Gjødesen, 2007). It is illegal for employees to clean the stables for more than 2-3 hours a day because of the harsh environment, unless they wear an oxygenated mask. Still there is a high risk of respiratory problems with the manual labour (Hiel, 2009).

Existing robot cleaners are preprogramed and unselective in their application of water. This means that it is only efficient to let them clean 60-85% varying across the sties, as set by the timers, followed by manual cleaning. This way only 13% extra water usage as compared to manual cleaning. Attempting to clean further with the robot will drastically increase the water waste (Gjødesen, 2007).

There are few attempts to make a computer vision sensor to provide feedback to the robot how clean the sties are (Braithwaite, 2005). However, these methods are limited to offline spectral analyses with no regard for structural information and the variable nature for the scenery at hand. For example, in a real stable the lighting will vary, steam will clutter the air, and the surfaces in the pigsties get discoloured by the manure. The goal in this paper was to develop and test a new computer vision algorithm that makes use of structural information for
pigsty detection and segmentation and a dynamic colour based approach for providing feedback on the cleaning process to avoid spraying water in vain on manure coloured surfaces. Andersen (2005) designed a process around a robot that relied on memory of the surfaces, but this has other implications. Instead, we propose an algorithm that can be used locally, align itself based on the vision ahead of itself, and would be easily employed in other domains.

Figure 1 shows a pig sty in its natural lighting. The lighting is not uniform and each surface material has different colour statistics.

Figure 1. [Left] Still dirty after the automatic robot had been there, while the neighbour sty was clean [Right] Clean. It still looked dirty, but it was discolouration of the concrete.

2. Material and Methods

The proposed algorithm is outlined in Figure 2. The robot uses the sensor to align itself in front of the pig sty. Based on the model it segments the surfaces (if applicable), and focusses the cleaning on a selected region at a time. Iteratively, it sprays and tracks changes, until no more changes are detected, based on the parameter “persistence”. In order to avoid misclassification due to running water and steam, a “wait” step with conditions (c) is inserted. The conditions used in this work were 1. No movement detected, and 2. Histogram match. Condition 1 removed errors from flowing water remains and condition 2 made sure that snapshots were taken with equal degree of steam.

Data acquisition was done with a low-cost Basler ACA640-GC with high dynamic range image computation in order to avoid saturation issues for the colour processing.

Two sequences were recorded: Sequence 1 simulating a robot moving from sty to sty for testing an automatic sty detection algorithm for centring itself during a cleaning process and segmenting the different surfaces, which are more or less tough to clean. Sequence 2 contained a structured manual cleaning process for testing the cleaning feedback vision system.
A 3D model of key features of the sty was generated in Google Sketchup and the model was fitted to the images for the segmentation and centering algorithm. See the model in Figure 3. This was the most robust model of many different models that was tested. It handled various occlusion issues and missing corner lines due to the manure. This model was also used to segment the different parts of the pig pen.

The actual cleaning consisted of 4 steps:

1. **Spray**
   In the experiment this was done manually and it was detected in the same way as the flowing water and steam detection using the double difference approach. The algorithm would then proceed to the wait state.

2. **Wait**
   After the spray the algorithm waited until the movements stopped and the image histogram aligned with the expected levels. See Figure 4.
3. Comparison (compute changes)

Changes before spraying and after spraying was done by dividing the region into cells in which pixels went from dirty colour to clean colour. Sometimes dirt was moved from one pixel to the other. These pixels were subtracted from the amount of pixels that got cleaned, such that dirt that got moved within the same cells did not count as a real change. This eliminated errors from small vibrations or dirt that was actually just moved a little. Real changes got marked as cleaned, or made dirty again. Overall it counted as a change. Parameter “persistence” defined the sensitivity to changes.

4. Decision

This step was the decision to move on to a new region or to keep cleaning. If cells within the region had changed for the better or the worse, it decided to spray again. Depending on “persistence” it would spray one more time if no change was detected.

Note for any given cleaning application, the performance of the above steps should be optimised such that the steam, movement, and dirt detection are done in separate monochrome colour-spaces that are uncorrelated to each other. This can be achieved by choosing a light source that has a colour orthogonal to the direction of colour space that defines the difference between dirty and clean areas.

Figure 4. Histograms of the entire image. [Left] Not misty [Right] Misty right after spraying. Once the conditions were met, the algorithm proceeded to the comparison state.

Figure 5. [Left] The pigsty pose was detected using 3D-2D pose estimation. It was able to detect whether it was there, and whether it was centred with 100% accuracy [Right] Segmentation of floor, sides, grates and lid.
3. Results

Figure 5 shows the pig pen alignment and segmentation result. Detection of the pigsty model was successful in all 6000 images and capable of detecting occlusion or when there was no sty in the image. The segmentation model could be used to label each pixel as floor, sides, grates and lid.

Figure 6 shows cleaning examples with three different settings of persistence in three regions. Persistence was a good way to control many burst of spraying was used, and the detection of change was accurate.

Table 1 shows the calculated water usage (in arbitrary water units) from the three different persistence settings and compare for three different regions how many times it chose to spray and when it was really clean. It is also compared to how many water units

Due to the iterative approach it will always spray one extra time to make sure there is no change. The wasted water can be limited by spraying more times in smaller bursts. It can also be considered that the sensitivity of the “change” detection should be separate from the persistence of spraying again after detecting no change in order to remove hard spots. Another parameter to set is the amount of water to use per burst.

<table>
<thead>
<tr>
<th>TABLE 1: Water usage as a function of persistence</th>
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<tr>
<td>Persistence</td>
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<tr>
<td>Needed steps</td>
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<tr>
<td>Steps area 1</td>
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<td>Steps area 2</td>
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<td>Steps area 3</td>
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<tr>
<td>Water units</td>
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<td>Clean?</td>
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4. Conclusions

This paper demonstrates a novel approach to cleaning applications, which is easy to adapt to different applications. It was easy to control with a single setting persistence. The segmentation of the surfaces enables a robot to target and focus on the hard to clean walls and grates. However, the dynamic strategy using colours and temporal changes would further enable intelligent cleaning with appropriately chosen stop criteria. The sensing approach was shown to have potential for saving water compared to a fixed setting in this experiment. Because the eating and drinking trays are able to turn themselves automatically it is not possible to achieve fully autonomous cleaning.

The proposed computer vision component can be used for an autonomous cleaning system in livestock buildings, transports as well as other kinds of cleaning where a change is visible to a camera. Future work should research the ability to detect biofilm as well.

Current work extends the solution to chicken farms and data has been acquired. It can also act as a component in a larger ICT system that monitors and optimises the environment in the livestock buildings and provides an interface for reporting the situation to the manager.

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References


