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Automatic Extraction of Droppers in Catenary Scenes

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Abstract

The aim of this paper is to present an automatic, image-based system for catenary maintenance, a novel application of machine vision which has no equivalent today. This study focuses on the detection of droppers in catenary staves. The system takes benefit from the fact that dropper location inside catenary staves follows mounting rules, an information that is integrated into a top-down approach in order to speed up and make reliable the extraction of droppers. Results obtained on a large database of real images are very satisfying and enable for continuing investigations for dropper fault detection.

1 Industrial background

Maintenance of railway infrastructure consists in checking the presence and the integrity of each element of the catenary stave. Today maintenance is carried out by visual inspection. The Innovation and Research Department of the French railways (SNCF) plans to automate this long and fastidious task. A dedicated acquisition system has thus been embedded inside a TGV coach [4]. The speed of the TGV being 320km/h, a high frame acquisition rate is required (53kHz). Thanks to a regulation of the obturation rate by the train speed, images are not fuzzy. Moreover, filters compensate for bad weather conditions. Images are acquired perpendicularly to the catenary. Their size is 1024x768 pixels and each pixel is coded on an 8-bit-gray level scale. For each image, the acquisition position on the line is provided. Horizontal resolution is 1.8 mm per pixel when the train speed is constant, but the resolution may vary during acceleration or deceleration.

Images represent adjacent segments of the catenary stave. A stave is made of about 40 images. A catenary stave is most often a single stave, with one pair of contact wire and carrying wire (Figure 1).

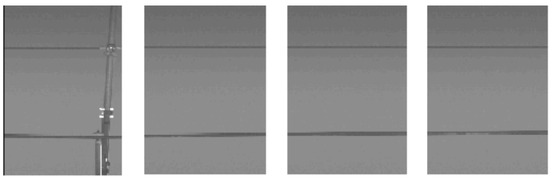

Figure 1: Successive images of a single catenary stave.

The contact wire provides electricity to train and the carrying wire supports the contact wire. Three vertical elements support the two wires: supporting arms, droppers and droppers with electrical connection (DEC). The part of the catenary that is delimited by two supporting arms is called a catenary stave (Figure 2). The number of elements and their position inside a catenary stave are specified in the so-called mounting rules.

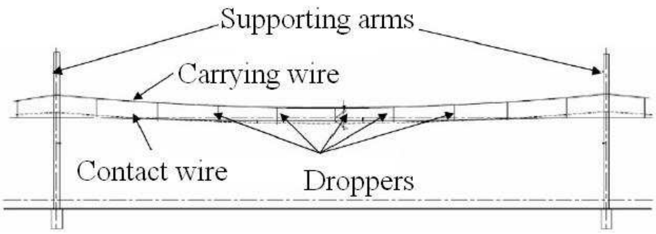

Figure 2: Overview of a catenary stave.

The aim of the study is to conceive and develop an automatic image processing system that allows to identify the catenary elements as described earlier, using the mounting rules. The ultimate goal will then be to detect faults on identified elements (typically, frayed contact wires, unusual objects on the catenary, broken droppers, faulty electrical connection on droppers...). In this paper we will solely focus on the dropper recognition part, as being a preliminary task to the fault detection process. Indeed, droppers are structural elements of the catenary stave and the knowledge of their number and type order is of crucial importance to identify the type of catenary stave we deal with. Conversely, using this knowledge to guide the dropper extraction process would ease the fault detection. Let us stress the fact that such an automatic analysis of the catenary droppers is an original machine vision application which has no equivalent today. To the best of our knowledge, only one similar system has been developed in the world: the work reported in [7] describes an onboard vision system for acquisition of catenary images in which automatic image processing is quite limited in that sense that catenary elements are identified manually before an automatic defect recognition is performed on manually isolated elements.

The remaining of the paper is organized as follows. In section 2 we justify the use of a top-down approach to extract droppers from catenary stave images and give an overview of the proposed system. We detail in section 3 the four steps to detect and classify droppers automatically and show how *a priori* knowledge can be used to perform a reliable detection of droppers; we give some experimental results on a significant database of real catenary stave images. We conclude in section 4 by some future works on this very challenging machine vision application.

2 Overview of the Proposed Approach

Identifying the catenary elements can be seen as a scene analysis problem, for which two main approaches may be used [1]:

- a bottom-up approach: simple, element-independent features are extracted from the image. These features are gathered and knowledge is incorporated into the recognition process in order to finally identify the objects.

- a top-down approach: this approach relies on the hypothesis that the image contains a particular object and thus consists in predicting the presence of features in the image, using high-level *a priori* knowledge.

The model in our application relies on the mounting rules which describe the different types of catenary staves. They indicate, for each type of catenary stave, the number and the order of droppers and droppers with electrical connection as well as the space between them (see for example Figure 4). This *a priori* knowledge can be very useful as it constrains the model that can be used to make the automatic detection of droppers more reliable. However, the model is not always fully applicable, i.e. not applicable on all catenary staves as horizontal resolution of the images may vary during acquisition due to train accelerations and decelerations. For this reason, we had first designed a bottom-up approach in which vertical and horizontal components were first segmented and classified without *a priori* knowledge, then checked and corrected through alignment of the whole stave models [5]. Though providing good results in terms of precision and recall in dropper extraction, this approach suffered from high computation time due to the fact that the analysis should necessarily be conducted on the whole image of the catenary stave. Therefore, we have rather turned toward the investigation of the top-down approach we report in this paper, in which *a priori* knowledge is used to guide the dropper extraction process.

An overview of our system is shown in Figure 3. The input of the system is a set of images representing the catenary stave. In this top-down approach, *a priori* knowledge is first used to roughly localize droppers. More precisely, subparts of the whole catenary stave image that may contain droppers are isolated thanks to geometric models. The most likely anchor points of each dropper are then detected on each local binarized image and characterized so as to discriminate between "simple droppers" and "droppers with electrical connections". A trellis of dropper hypotheses (dropper classes along with their probabilities) is then analyzed to search for the most likely path through the alignment of dropper sequence models of catenary staves. The output of the system is a sequence of dropper locations and classes that will be used in a further step for defect detection.

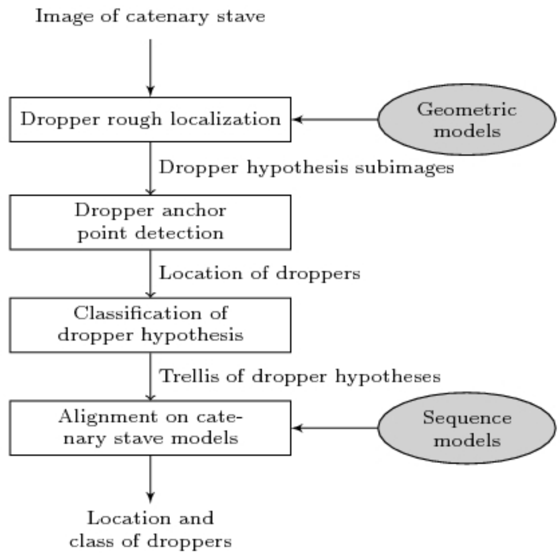

Figure 3: Overview of the proposed system.

3 Automatic Detection of Droppers

We now detail in this section the four steps of our top-down approach to detect droppers. Let us recall that the input of our system is a whole image of a catenary stave obtained from the concatenation of single images. Typically, the whole image is 30000 pixels long made up of the concatenation of about forty 1024x768 images (typically a 1.38m-long subpart of the catenary).

3.1 Rough localization of droppers

In this first step, *a priori* knowledge about mounting rules is used to limit the search for droppers to the most likely subparts of the whole image and thus to provide hypotheses of dropper locations without needing a "blind" analysis of the whole image. Note that each catenary stave must respect specific mounting rules that set the distance between two consecutive droppers depending on the length of the catenary stave as shown in Figure 4.

The database of catenary models contains 74 types of stave or models ranging from the simplest one made of a sequence of 4 droppers to the most complex made of 15 elements combining droppers and droppers with electrical connections. Therefore, one way to limit the search for droppers is to filter this database of catenary models by estimating the distance between two supporting arms, i.e. the length of the catenary stave [4, 5]. This length acts as a discriminative feature that enables to predict roughly the location of dropper hypotheses and thus to segment the whole image of the catenary stave into those subparts of the whole image that contain a dropper. Note that due to small train accelerations and decelerations during image acquisition, width of the subparts of the whole image that will be further analyzed in the next step is chosen large enough to take into account possible variations of horizontal resolution (typically 1500 pixels).

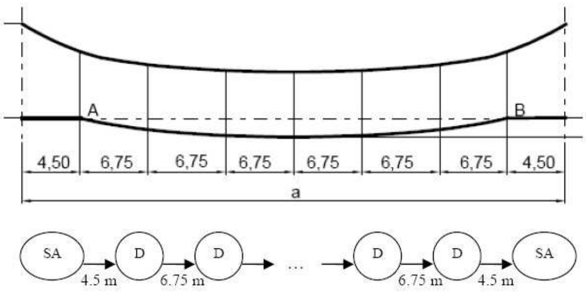

Figure 4: Mounting rules of a 63m-long catenary stave made up of 7 droppers (D) and its corresponding geometric model defined by the inter-dropper distances between two supporting arms (SA).

3.2 Detection of dropper anchor point

The input of this stage is a subpart (1024x1500 pixels) of the whole image segmented from the dropper rough localization stage, where a dropper is assumed to be present. As the elements of the catenary are quite linear, they may thus be detected by thresholding horizontal and vertical projections of the image. But images are not as straightforward to process as they seem. Indeed, they show inhomogeneous noisy background, that has a poor contrast with the droppers. Droppers are also very thin, only 2 to 3 pixels wide. Furthermore, some objects are darker and some other are lighter than the background (Figure 5). Note that for visualization purposes, all images presented in this paper have been manually contrast-enhanced.

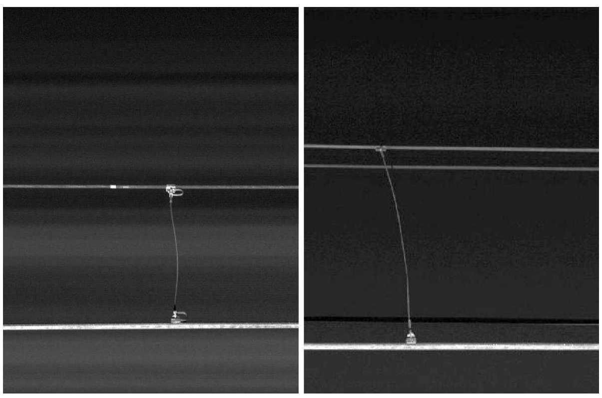

Figure 5: Dark and light objects in a catenary stave.

In order to simplify the anchor point detection process, the image is binarized. Because of the background inhomogeneity, binarization is performed using TopHat and BotHat morphological operators (Equation 1). The TopHat (respectively BotHat) operator allows to segment elements which are lighter (respectively darker) than the background [6].

$$\begin{array}{l} TopHat = Image - Opening(Image) \\ BotHat = Closing(Image) - Image \end{array} \quad (1)$$

The two structuring elements for these operators are constructed according to the shape and the size of the elements to be detected. They are 10-pixel long horizontal and vertical lines.

A binarization result is shown on Figure 6.

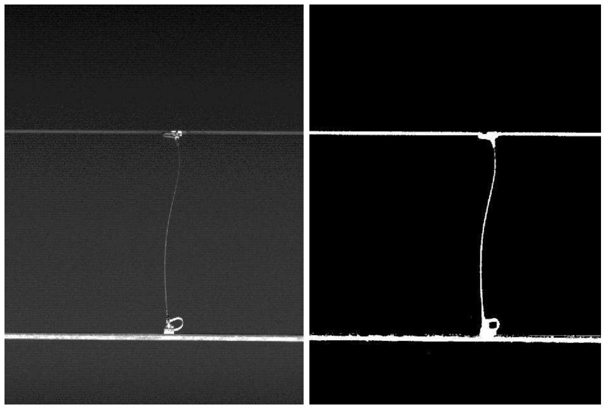

Figure 6: (left) Original image, (right) Binarized image.

Segmentation into vertical and horizontal components is then performed by thresholding the projections of the binarized image along both directions:

- vertically, in order to detect vertical elements (supporting arms, droppers and droppers with electrical connection) ;
- horizontally, in order to detect horizontal elements (contact wire and carrying wire). Since the wire horizontality is not always maintained, the rotation angle is taken into account before projecting the image, by means of a Radon transform [3].

By intersecting vertical and horizontal elements, two dropper anchor points are thus localized in the binarized image.

3.3 Classification of droppers

To discriminate between simple droppers and droppers with electrical connections, one can observe in Figure 7 that difference between these two elements is simply the presence of a larger area of pixels at wire-dropper intersection in favor of droppers with electrical connections. A 2-feature vector based on pixel densities extracted from the neighborhood of each anchor point seems therefore to be discriminative enough to classify droppers.

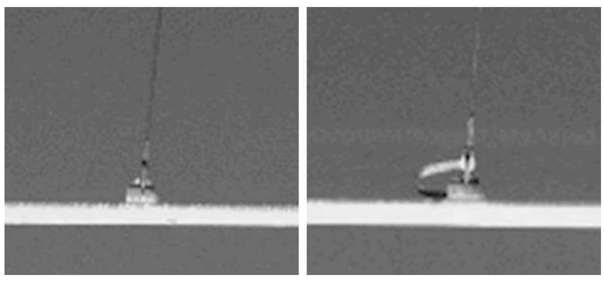

Figure 7: (left) Simple dropper, (right) Dropper with electrical connections.

Classification of droppers is performed by a 2-5-2 MLP. This classifier has been chosen because it is fast in decision, provides good generalization properties, and can output posterior probabilities for sequence model alignment [2]. The output of this stage is finally a sequence of classification hypotheses, each one associated with a posterior probability. The next stage will consist in correcting the possible errors of classification by aligning various models of dropper sequence.

3.4 Alignment on catenary stave models

In a top-down approach, recognition is mainly a verification step that searches for aligning models on observation sequences output by the classification stage. Therefore, the alignment of the catenary stave models consists in searching for the optimal path through dynamic programming for example. In our case, it simply consists in multiplying probabilities provided by the MLP-classifier through model paths. The winner path is that one with the highest final probability as shown in Figure 8.

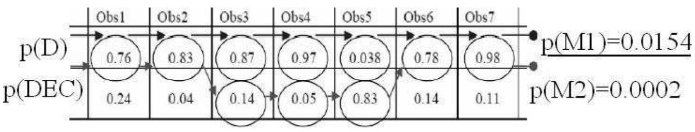

Figure 8: Alignment on the MLP results of two catenary stave models made up of 7 droppers: M1 with 7 simple droppers (D) and M2 with 4 simple droppers (D) and 3 droppers with electrical connections (DEC).

3.5 Experiments and results

Experiments for dropper detection have been conducted on a database of 689 whole images of catenary staves representing in total 5161 droppers to be detected, for which the ground truth has been obtained by manually tracing a bounding box around the droppers. Image base is split into:

- a learning base (474 catenary stave images) : 2752 droppers, 803 DEC ;
- and a test base (215 catenary stave images) : 1262 droppers, 344 DEC.

Let us stress on the fact that the dropper rough localization succeeds in segmenting the whole images of catenary stave into subparts containing a dropper (either simple or with electrical connection) with a 100% segmentation rate. As for the correct dropper recognition rate is concerned, Table 1 presents the performance of our system before and after model alignment. As one can see, the correct classification rate before alignment (MLP solely) is pretty good for simple droppers but is somehow critical for droppers with electrical connection. That comes essentially from the binarisation of the segmented subparts of the whole images that introduces some spurious densities of pixels around the anchor points. However, the performance of our system after model alignment are quite satisfying and allow the French Railways to now investigate fault detection on catenary staves.

Table 1: Correct classification rate

	Before alignement	After alignement
Simple droppers	99.36%	99.68%
DEC	95.93%	99.13%
Average on droppers	98.62%	99.56%

Recall and precision rates are also two widely used measures for assessing the quality of results of detection and information extraction tasks.

- recall, which is a measure of the ability of the system to localize and recognize all presented droppers, is 99.06% ;
- precision, which measures the ability of the system to provide only correct hypothesis and thus to limit the number of false alarms, is 99.06%.

Both rates are satisfying and show the good performance of our system.

4 Conclusion and perspectives

We have presented in this paper a top-down approach to automatically extract droppers from catenary stave images and have shown that *a priori* knowledge can be used to perform a reliable detection of droppers. The experimental results obtained on a significant database of real catenary stave images have demonstrated the interest of our approach which is an original and real machine vision application that has no equivalent today. Future works on this very challenging machine vision application will deal now with defect detection, particularly some complex tasks such as real-time detection of frayed contact wires, of unusual objects on the catenary, of broken droppers, or of faulty electrical connection on droppers.

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