ANALYSIS OF THE RECOGNITION AND LOCALIZATION TECHNIQUES OF POWER TRANSMISSION LINES COMPONENTS IN AERIAL IMAGES ACQUIRED BY DRONES

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ABSTRACT

This article presents an analysis of the processing techniques for the recognition of components in aerial images done by Unmanned Aircraft System (UAS or drones) on power transmission lines (TLs). The objective is to elect efficient techniques of easy programming, whose application, in the final user work field, demands little knowledge of image treatment by the technicians involved in the operation or future expansion of the system. This work is part of a project on industrial improvement by the Institute of Energy Studies and Management – INERGE and by Celesc Distribution, whose main goal is to develop an integrated system UAS for automated inspection of AERIAL transmission lines. The automated inspection process was divided into the stages of recognition, localization and evaluation of components through the analysis of TL images. The two first stages are explored in this work using the methodology of bibliographic research of different techniques of recognition and evaluation of components, comparing their capacity and characteristics, especially the efficiency and simplicity of the techniques' application. Some of these, which had not been applied to the recognition of components of TLs, were tested in this work, such as the use of Profound Neural networks, the extraction of attributes by Speeded Up Robust Features (SURF) and Bag-of-Words (BoW) using Support Vector Machine (SVM). In an experimental research approach, algorithms were implemented for this test using three types of components: power towers, suspension and strain type insulator strings, whose evaluations used real LT images defined for the project trials. The results of the comparison were collected and measured through statistical analysis presenting the rate of accuracy for the components tested with values between 85% and 92%, which are considered to be very good for this type of application. The final objective of the solution will be to allow the building of an efficient and robust system for the recognition and inspection of components in the transmission lines and at the same time attach simplicity to the operational process, allowing updating and expansion of the recognition capacity for other types of components.

INTRODUCTION

The concept of electrical systems autonomous inspection using aerial images and Unmanned Aircraft System (UAS is relatively recent, introduced by Campoy's work [1], in 2001. The subject has gained attention and supports research projects developed in the last years [2], [3], [4], [5], [6], besides enterprises initiatives in Austria [7], China [8], Finland [9], the United Kingdom [10] and the United States [11].

In literature, the techniques developed are presented aiming the recognition of a type of component in the electrical system, for example, the works [2], [12] and [13] explore identification of the transmission lines conductors, [14] explores the identification of towers, [15] and [16] explore the identification of insulators strings.

Besides the methodology and inspections procedures, it is essential to select and explore just a single tool. It must be capable of identify new components with simplified developments and minimized effort of adaptation. It will allows company technicians execute future maintenance, updating and expansion of system in uncomplicated manner. In addition, without any expertise education as digital image processing. This quality is essential for the systems maintenance by Celesc IT team, after the end of the project.

APPLICATION ARCHITECTURE

The system designed to reach the goals is multi-specialized and made of the integration of aeronautic and avionic engineering, telecommunications, information technology, image processing, and power systems engineering. In spite of its complexity, figure 1 presents a simplified diagram of the blocks that represent the many processes and interactions within systems. The images are acquired through a UAS programmed to fly over part of the transmission line under a pilot's supervision. These are kept in a disk and physically passed to the ground station system which, besides doing the flight control and logistics, executes evaluations about the quality of the acquired data. When satisfactory, the data are sent to the company's processing center, via a data network, at the end of the field stage. The data is automatically inspected in the server and the results are available for interaction with the specialist technicians in the operations center.

The interaction is very comprehensive and allows a second opinion of the evaluation of the highlighted points identified by the automated inspection system, the historical analysis of the points' evolution, navigation between network elements and classification of new defects, amongst others. At the end, reports organized by the system will allow for the optimized planning of the field maintenance works, better prediction of many sectors

involved such as purchasing, work team recruiting and even the company's business intelligence team. The system is also made flexible by the use of WEB and mobile platforms.

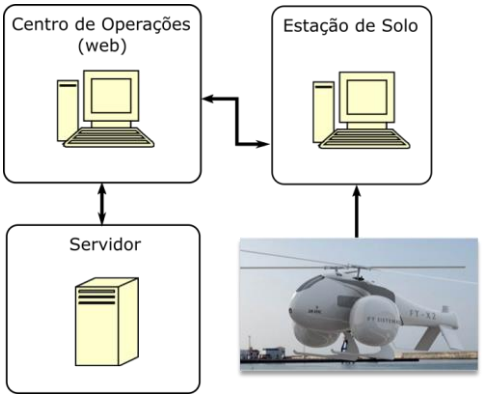

Figure 1 - General architecture of the automated inspection system

DEVELOPMENT

Development of recognition tools, localization components processing up and clarity index is addressed.

Transmission lines components recognition tool

Because it is the basis of the entire inspection system, the object recognition function has a more detailed explanation subdivided in bibliographic review, proposal, tests and results evaluation, as follows.

Bibliographic review

Object recognition is the primordial step in the processing and must consider the identification and classification of the many components, which may be changed in its characteristics throughout the life of the system. Techniques which present versatility and generic attributes, based on learning of combined machinery with attributes extraction such as in [19], [14], [20], [15], [16], may reduce development time and allow for a simplified application process making the technology transfer and personnel training easier. These techniques have advantageous aspects for the project and can reach the aimed goals.

Amongst these, Wu [19] recognizes insulators strings using Support Vector Machine (SVM) as classifier, attributes extraction from multilevel threshold, proposed by Otsu, in 1979 (Wu [19], page 4), and of the horizontal projection derivative and coding in areas of maximum and minimum along the longitudinal axes of the object's regions. Sampedro [14] uses Artificial Neural Networks (RNAs) for classification and extraction of attributes by HOG [21] in the location and classification of transmission line towers. Oberweger [20] proposes the recognition and evaluation of insulator strings using a function based on SIFT [22], however, incorporating gradients from the orientation and color histograms, the classification being based on RNAs. Zhai [15] proposes, also for insulator strings, recognition by Haar [23], with an attribute extractor based on Wavelet and a heuristic classifier AdaBoost [24]. More recently, Liao [16] performs the insulator strings recognition with attributes extraction by a detector based on Harris, describer proposed by Oberweger [20] and classifier based on K-means and Spatial Orders Features (SOF).

All works presented good efficiency, with a success margin between 85% e 92%. However, putting the aimed goals into context, the proposal by Obeweger [20] demands a level of mathematics excessively complex for a simplified process. Zhai's solution [15] demands a great number of images and extensive training period. In addition, even though the technique presented by Liao [16] shows efficiency, it presents mathematics that is too complex for the project's objective.

Wu's [19] and Sampedro's [14] articles use Support Vector Machine (SVM) classifiers and Artificial Neural Networks (RNAs) that have broad adherence by the software developers' community contributing to the technology transfer and the promptness in tools development. For the attributes extraction, Wu [19] developed a detector that depends on the image's position, considering horizontal and vertical lines, which reduces the strength of the final application. Sampedro [14], however, opted for using Histogram of Oriented Gradients (HOG), which besides being efficient, influenced the development of many other techniques such as Scale-invariant feature transform (SIFT), Speeded up Robust Features (SURF), and Feature from Accelerated Segment Test (FREAK).

Proposed solution

Considering that, the above-mentioned techniques may have small differences between them in regards to efficiency, the choice for the project lands on the aspect of popularity and simplicity of implementation. Consequently, SVM and RNA stand out as classifiers and HOG for attributes extraction. These are traditional techniques and have evolved in the last years. With SURF e Bag-of-Words (BoW) standing out in replacement of HOG in the attributes extraction because of its better performance in processing time.

In spite of being largely used in the area of patterns recognition, up until now, SURF+BoW still have not been explored in applications specifically for electrical transmission lines components recognition.

Although it has been mentioned in Liai [16], the BoW technique was not addressed in that work.

The project started with a study using as the basis for the recognition system an algorithm that applies attributes extraction through SURF e BoW and performs the components classification by SVM. The solution allows the recognition of many types of components and up until now there haven't been found any works which show the application of these techniques on images of electrical

transmission lines components.
The techniques SURF, BoW and SVM were implemented using the language C++ and the library OpenCV [25], chosen for having an active development and cooperation community and for providing efficient functionalities.

Tests
Tests verified the recognition of three types of components: High voltage towers, strain and suspension insulator strings. For this purpose, recognition sessions were made which covered: tool training, with positive and negative stimulus and, later, verification. All images were manually cut from real aerial scenes, acquired for the test, while background scenes were used as negative stimulus for all the training. Table I presents the number of images used for the training and components recognition verification steps. Figures 2 present examples of the images used for training in function recognition.

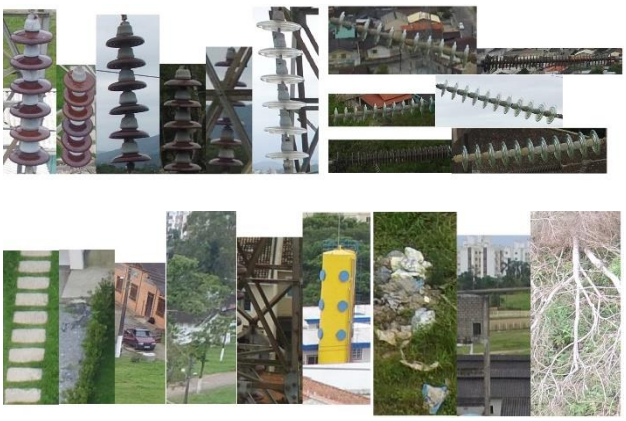

Figure 2 - Example of images used to algorithm training. Upper image shows insulator strings and lower image shows scenes background.

Five recognition sessions were performed: multi-class recognition with two class of insulator string: suspension and strain; binary recognition of strain insulator, suspension insulator and towers, with reduction in dimension of the towers. The data of interest collected in these tests were: success rate (%), average image size (kilo pixels) and recognition processing time per image (milliseconds), of which the results are presented on table II.
The stratified method of estimation by retention (holdout) was used for validation due to the limited amount of data. (2/3 for training and 1/3 for verification).

Results and Discussions
The recognition of Towers (tab. II, item 1) presented the highest efficiency in relation to the success rate compared to the insulators string recognition (tab. II, items 3, 4 e 5), an expected fact as it has a larger number of images for training than the other sessions. The time for towers processing (tab. II, items 1 e 2) showed to be proportional to the size of the images, without losing efficiency, by the way, comparable to the highest success rate in the mentioned articles, presented by Liai [16].

Table I - – Number of images used for algorithm training and verification

Image classes	Used in training	Use in verification
Tower	33	9
Tower images background	50	12
Suspension insulator string	19	8
Strain insulator string	18	7
Insulator string images background	29	8

Table II – Test classes and results, showing image size influence in processing times.

Recognition processing sessions	Recognition (%)	Image Size (k pixels)	Time of processing (mSec)
Tower	91.3	328	897
Tower - smaller image	91.3	89	242
Suspension and strain insulators	80.1	100	533
Strain insulator	92.8	71	772
Suspension insulator	85.7	112	719

In the insulators recognition, when sessions which verify two classes of insulator strings were executed (tab. II, item 3) the success efficiency was a little reduced if compared to sessions executed separately with each class of string (tab. II, items 4 e 5). On the other hand, the time for recognition was shorter than in the sessions executed separately, in spite of the size of the images being almost equivalent.
Lastly, it is verified that the implemented tool has characteristics, which can satisfy the project's needs, after demonstrating its efficient capacity of recognition in more than one type of transmission line component. The recognition of other types of components may be reached without the need for alterations or adaptations to the code, the SVM training being sufficient using the collection of positive and negative images.

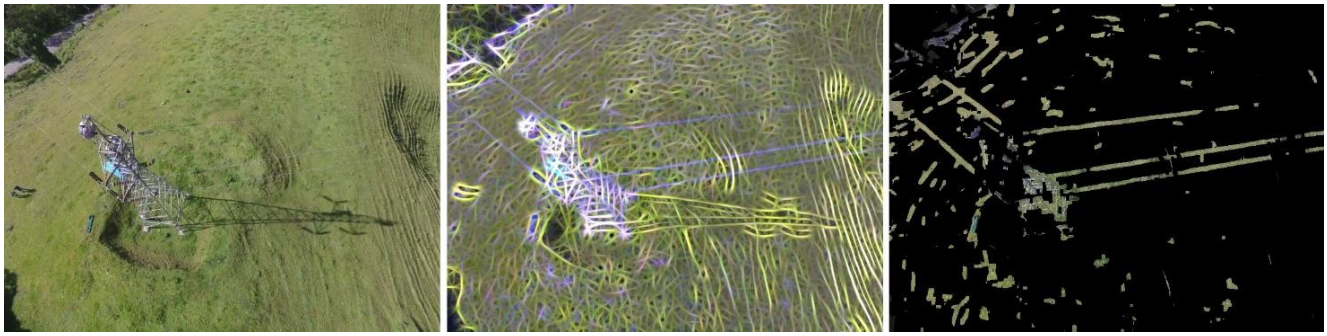

Figure 3 – Gabor filter and Threshold applied gradually as example

Speed the components localization up

The recognition algorithm uses windowing technique, performing a complete sweeping on the image. To increase its efficiency, a filtering algorithm was developed based on the characteristics of the object's points of interest, in a manner that the sweeping through windowing is executed only on regions with the bigger probability of occurrence of the searched object.

In a first analysis, the objects searched on the images are tower, cables and right of way. The structural characteristics of these objects stand out because of the application especially parameterized of a linear filter called Gabor filter. The use of this filter allowed us to segment the image into regions of interest and in this way to execute the sweeping in search of the objects only on specific areas of the image.

The filtering uses a parameters configuration inserted in a Kernel Gabor filter. This configuration was reached through the use of different parameters in the test phase. From these tests, the results were collected for the performance of statistics analysis relating to the attained accuracy. Figure 3 shows a processing example.

Two factors were relevant for the accuracy measurement. The first factor was the amount of low interest regions for the search of the object that the algorithm was able to remove from the image. The second factor was the index of the high interest areas that were removed by the algorithm and that should not have been removed. In the end they arrived to a configuration of parameters which resulted in a reduction factor of 70% to 85% of the sweeping area over the original image.

Image clarity evaluation technique

A process that calculates a clarity factor of the images was included in the system with the purpose of providing the system's outfield operators with information on the quality of the acquisition of the images and consequently of the operation as a whole.

According to Peach-Pacheco [26], an efficient technique of low computational cost in comparison with others is the Laplacian variance calculation to obtain an image clarity index. Through statistical analysis, one can arrive at a threshold clarity factor, in which the images that result in a clarity index higher than the clarity threshold of 100, are considered as good clarity. Images that result in a clarity below 100 are considered blurred.

The results allowed the clarity degree of the image to be obtained with efficacy and efficiency. This information indicates if the image can be used for detection and recognition of objects and also aids in the identification of some factors related to the conditions of the operational equipment for image capture. An image without clarity may demonstrate a fault in the equipment or in its configuration, on which the operator should perform a verification to assure it is working without faults.

CONCLUSION

The proposed solution allows a strong and efficient system for recognition of the transmission lines components to be built, and at the same time add simplicity to the operation, as well as updating and expansion of its recognition capacity. The transmission line inspection with the aid of UAS is a worldwide tendency and this article aims to enrich the discussions and advances on the subject.

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