Autonomous Plant Inspection and Anomaly Detection

M. Gregori+, L. Lombardi+, M. Savini+, A. Scianna*

+University of Pavia, Dipartimento di Informatica e Sistemistica
Via Ferrata 1, I-27100 Pavia, Italy
Phone: +39 +382-505350
Fax: +39 +382-505373
{gregori,luca,savio}@ipvvis.unipv.it
*ENEL/CRA
Via Volta 1
Cologno Monzese (MI), Italy
scianna@cra.enel.it

Abstract. We here present some results of an applied research work dealing with the problem of autonomous inspection in power plants. The aim of this effort is to actualize a qualitative and quantitative improvement over the methodologies currently adopted in routine plant reliability and safety operation. We want to reach this target by exploiting the advantages of the active approach to machine vision, the currently available robotic techniques, and the enhanced value of linking the robot to the plant informative system.

1 Introduction, Problem Description & State of the Art

The great majority of working or attempted applications dealing with autonomous robotic systems in power plants have been developed in the nuclear domain. This is due to the particularly hostile post-accident environments that can actualize in those plants. It is much more difficult to find deployed applications of autonomous robotics in conventional thermoelectric power plants. This does not mean that robotics has no place in conventional power plants. On the contrary, many of these plants are less "clean" and much more in need of automatisation than their nuclear counterparts. In fact, in the majority of plants, the management actually feels the need for reliable robotic solutions to inspection and surveillance problems, but they find several obstacles on the road to their actual implementation.

The first one is the lack of widespread commercially available autonomous robotic solutions to the problem. This is mainly due to the poor performances of current vision systems in general object recognition and scene interpretation tasks. This does not mean that we do not have good vision systems around. We could list several systems that have achieved impressive performance figures [1] if compared with systems of, say, ten years ago. There have been also new approaches to computer vision that have provided us with better solutions to old and new problems [2]. One of the most successful among them has been the active approach to vision [2], but the major breakthroughs achieved by active vision have been in navigational tasks [3-5]. This is of course a precious contribution to mobile robotics, but the inspection problems in power plants have much more to do with anomaly detection and object recognition than with navigation. We could actually imagine a complete autonomous inspection system based on robots running on tracks, or even based on a collection of fixed cameras with pan, tilt and zoom capabilities. Nevertheless we think that also recognition problems will benefit from an active approach [6,7].

Another obstacle to the development of autonomous inspection systems is the great variety of plant configurations and environments. Difficult to reach locations often call for ad hoc and costly mechanical projects. Nevertheless these locations, along with hostile environments, are the main reasons behind the quest for robotic solutions. Beyond risk, personnel costs for carrying out extensive routine inspection is another reason that can push automatic inspection and surveillance. But at the same time unemployment problems are an obstacle to the automatisation of some routine jobs. Other difficulties arise because current plants have not been built with automatic inspection in mind. This makes it hardous integrating new solutions [8].

2 Automatic Visual Inspection and the Plant Information System

Plant control and supervision are usually managed by either two separate real-time computer systems or a fully integrated one. The control system, connected point to point or through a field bus to the plant, collects all process data needed by its control loops to operate the plant. All extra data, like metals temperatures, vibrations and noises, are collected by the supervisory system; this second set of data allows the operator to monitor plant conditions in real time and to preview risk situations. Presently information is collected by traditional sensors that measure physical quantities, like pressure and temperature, without any particular elaboration. They are characterized by a high or low accuracy and precision, and they can range from cheap and simple thermocouples to expensive and sophisticated chemical sensors.

An artificial vision system can be considered an advanced and sophisticated sensor. It can acquire and process images with many different algorithms, so to extract many kinds of task dependent information. This flexibility alone makes a powerful diagnostic tool of it, but if you couple vision with robotics you will pour the same capabilities into an ubiquitous, location dependent, diagnostic tool.

The problem is how much we can rely on measurement results from such a sensor. As with other sensors, we need to characterize them with accuracy and precision but, even more important, with reliability. What we can expect from vision sensors in these terms will determine the use we will be able to make of them. A first weaker use could be in the supervisory system data base to support operator decisions for a better and safer plant operation. In a stronger way it could be considered as an input to the plant control system. Visually gathered information could represent an alarm signal in the control room alarm system or an input signal for a plant maneuver. This operation could be carried out either by plants components such as valves and pumps or by a robot. In this case the robot would be used as an actuator. This integration in the control system represents a huge improvement in plant operation.

At the end we can say that in many plant situations we have examined either traditional sensors can not be used or they result to be more expensive than thoughtfully designed vision systems. For what concerns some visual inspection tasks, personnel is currently loaded with periodical duties that cannot be made more frequent. In these cases an on line vision system would provide all the advantages of continuous monitoring.

3 Proposed Approach

In our approach a collection on vision systems should be integrated with the plant data acquisition system. They should be either intelligent sensors dedicated to some critical point of the plant or more flexible vision systems that a robot can move around. The improved flexibility and power of the mobile system are necessary for both navigational tasks and the many recognition tasks that it has to perform. Of course, navigation is much easier if the robot runs on tracks or on some constrained path. The increased possibilities provided by mobile systems stem also from the active vision techniques that we can implement with them.

The integration between machine vision and the plant informative system is even more important for mobile robotics. Vision-based positioning can be useful for navigation, but it becomes even more critical for object recognition and scene interpretation. It does not matter if we use Landmark-Based [9-12] or Model-Based [13-15] approaches to positioning: all of these methods require some knowledge of the structure and geometry of the viewd scenes. New plants, computer aided designed, can keep their CAD data base online in order to provide both improved interfaces to plant operators and model knowledge to robots and intelligent inspection systems. If we do not have such CAD data base we nevertheless may have topological and functional schemes that, along with Feature-Based Visual Map Building [16-18], can strongly aid an autonomous inspection system.

4 Three Steps Toward the Solution

The following examples describe the first three inspection problems that we have studied and solved. Field tests have been conducted with good results and their permanent installation in some production plants is in the project phase. The integration with the plant informative system that we are proposing is at the supervisory system level. Other solutions to different inspection problems are currently under development.

4.1 Residual Water Pool

The first test case is the inspection of a residual water pool to detect excess oil percentage on the water surface (see figures 1a, 1b, 1c). This is accomplished by measuring and monitoring the amount of oil on the water surface and it represents an important real-time process control problem. A high volume of oil means a dangerous plant operation and sometime, without a timely countermeasure, a complete plant shut down. When we looked at the images we got from the plant, we promptly realized that a real problem was to discriminate between "normal" and pathological situations. The problem is that there is always some oil on the water surface but, depending on the quantity of it, this might be either considered normal (fig. 1a) or an index of a really critical situation (fig. 1c). So, it is neither sufficient nor meaningful to detect oil presence on the water surface but we needed to quantitatively estimate it.

As a simple solution, a threshold could be set to determine the alarm level over which we need operator intervention. We judged a better approach to provide the operator with the temporal evolution of the measurements performed on the visible parameters of pollution. Only if all the quantitative parameters are available the operator can assess the risk for economic plant operation. Presenting the history of performed measurements allows an easier calibration of the important thresholds.

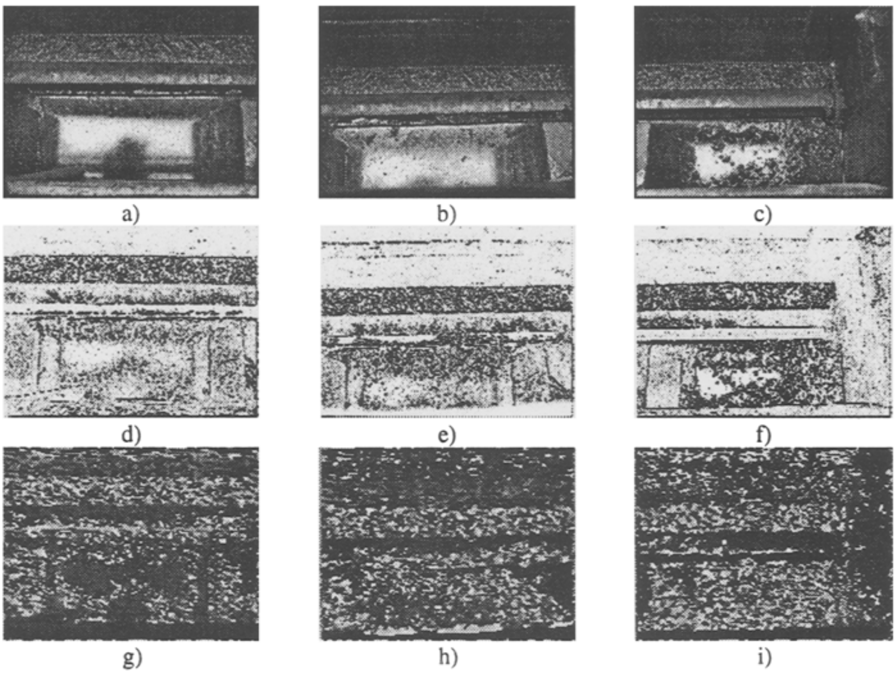
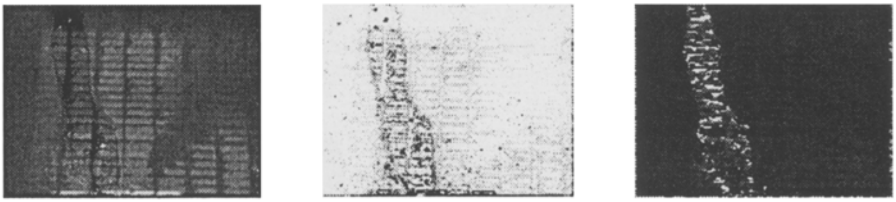


Fig. 1. Residual water pool: a), b) and c) are normal, somewhat dirty and critically dirty water contitions respectively; d) - f) show the unprocessed output of edge operator; g) - i) show the chrominance.



a) b) c)

Fig. 2. Residual water pool: a) is the original image showing an oil leakage; b) shows the edges; c) shows the chrominance.

Possible features that must be detected are oil leakages (fig. 2a), bubbles and iridescent regions on the water surface (figures 1b, 1c). In normal condition the water surface in the pool appears as uniform, without bubbles or evident flows. As a preliminary analysis, edge detection is performed to identify discontinuities due to bubbles on the liquid surface. Further analyses consider saturation and chrominance to identify differences between oil and water reflection characteristics [19].

Edge detection performed on the intensity image put evidence on leakages and bubbles. This suggested that we could measure this kind of features by edge point counting. Gradient thresholds have been selected in order to match the amount of edges to the perceived "granularity" of water surface. In this way images acquired in standard conditions carry almost no edges.

A second test measurement performed is saturation analysis. In presence of oil on the surface, where reflections are colored, this analysis detects higher values than in standard conditions. In particular, if oil completely covers the surface, the difference is remarkable. On the other hand almost clean surfaces may produce false results, because of the high saturation values produced by colored reflections on the water. Saturation analysis can easily differentiate between extreme situations, but it fails to detect a weak anomaly.

Chrominance analysis produces good results, too. Dirty but dry walls and pipes surrounding the pool show chromatic components between green and red, that correspond to values in the range 0-0.33, in our scale representation of the hue image, as shown in figures 1g-1i. Wet walls and pipes appear blue or red, and correspond to values in the range 0.6-1. Blue components are produced by oil dirty water drops, shadows and light reflections, so inspection of water surface is a complex problem, due to reflections of surrounding walls and pipes on the surface itself. Nearly clean water shows a colors distribution in the red range, while dirty water spans a wider range. The more dirty is water the more the hue histogram center shifts toward the blue color. As a conclusion, oil presence corresponds to high saturation and a blue centered hue distribution.

Our approach consisted in integrating edge detection on the intensity image with hue distribution analysis. We exploit the result from chrominance analysis as a weight to decrease or increase edge detection thresholds. In addition, a masking operation based on hue distribution values selects only edges that are more probably inside an oil covered region.

We devised a simple calibration scheme that can be performed by uninformed personnel at the plant. This scheme can adjust the calibrated parameters in line according to the results of routinely performed analyses.

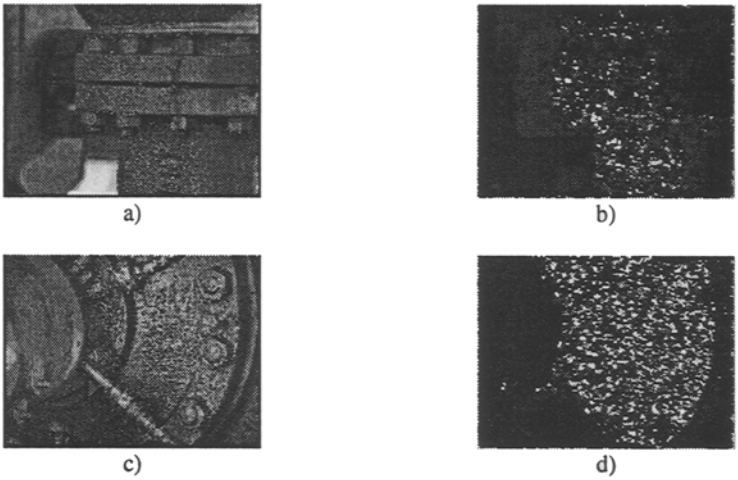


Fig. 3. Booster pump: a) and c) are the original images; b) and d) show the chrominance.

4.2 Booster Pump Leakages

The second test case is represented by oil leakage identification on oil feeding pumps (booster pumps). Figures 3a and 3c show oil drops on pump surfaces. This phenomenon is a first clue of a possible important plant damage. Also in this case drops show clearly visible iridescences, so the same methods exploited by chromatic analysis in the residual water pool test case can be used. The results are quite accurate and are shown in figures 3b and 3d. In this case edge detection is not useful due to the pump complex shape and to the consequent presence of many misleading edges.

4.3 Steam

The third problem we faced is the detection and measurement of steam puffs. There are places in the plant where a small continuous flow of steam is normal, but occasionally the flow gets stronger. This gives information on possible malfunctioning upstream components or subsystems. But unexpected steam leakages actualize also in places where they should not. A timely detection is in these cases very important for plant safety, availability and efficiency.

Steam is a kind of object that cannot be characterised by shape. Its visually salient features are colour and motion. In addition it is generally hot.

Image regions where steam is present are generally lighter than the surrounding regions because of light reflection. This has a desaturating effect on the color of objects and regions transparently occluded by steam. Of course the degree of background masking depends on puff thickness along the line of sight. At a certain point the masking becomes total. For this reason we focused our attention on light and desaturated regions of the image. We can greatly improve the selectivity of this kind of analysis by mounting a suitably oriented polarizer on the camera lens. In fact highlights produced by light reflection on liquid or other strongly polarizing surfaces share these same features with steam. The effect of the polarizer is strong on these reflexes because they are already polarized. At the same time the effect on light coming from steam is negligible.

On one hand, the continuous aspect variation of puffs makes steam such a variable subject that it is very difficult to characterize it morphologically. On the other hand, this variability is precious for detection. By analyzing image sequences taken from a fixed point it is easy to locate moving objects by simple frame difference [20]. Of course, by this technique, we detect any moving object. So it is necessary to integrate the results of motion analysis with that of color analysis.

A further contribution to the accuracy of our steam sensor could come from the use of infrared cameras. The high temperature produces stronger signals in infrared images, making steam, as well as other hot objects, distinguishable from cooler objects.

5 Conclusions and Future Work

In this paper a mobile robotics system for autonomous plant inspection and anomaly detection has been proposed. The overall problem may be decomposed in several steps. Three test cases have been analyzed and solved.

At this moment we are working toward other inspection problems that are even less structured; as an example we are developing an active vision approach for the detection of oil pools, optical and mechanical parameters of a camera mounted on a robot are actively controlled in order to obtain an accurate measure of the pool.

In the meantime we are starting to integrate our vision systems with the plant informative system at the supervisory level.

6 References

1. E. D. Dickmanns, B. Mysliwetz and T. Christians, "An integrated spatio-temporal approach to automated visual guidance of autonomous vehicles", IEEE tr. on SMC, vol.20 (1990), pp.1273-1284.
2. J. Aloimonos, I. Weiss and A. Bandyopadhyay, "Active vision", Int. Jou. of Computer Vision, vol.1, (1988), pp.333-356.
3. A. Blake and A. Yuille eds., "Active Vision", Cambridge, Mass., MIT Press (1992).

4. R. Sharma and J. Aloimonos, "Robust detection of independent motion: an active and purposive solution", CAR-TR-534, Univ. of Maryland (1991).
5. C. Fermuller and J. Aloimonos, "Tracking facilitates 3-D motion estimation", CAR-TR-618, Univ. of Maryland (1992).
6. K. N. Kutulakos and C. R. Dyer, "Recovering Shape by Purposive Viewpoint Adjustment", Int. Jou. of Computer Vision, v.12 n.2/3, (1994), pp.113-136.
7. K. D. Gremban and K. Ikeuchi, "Planning Multiple Observations for Object Recognition", Int. Jou. of Computer Vision, v.12 n.2/3, (1994), pp.137-172.
8. Timothy S. Newman, Anil K. Jain, "A survey of automed visual inspection, Computer Vision and Image Understaning, Volume 61, N.2, pp.231-262, Academic P, Marzo 1995.
9. Sugihara, K., 1988, "Some Location Problems for Robot Navigation Using a Single Camera." Computer Vision, Graphics and Image Processing, vol. 42, no. 1, pp 112-129.
10. Krotkov, E., 1991, "Mobile Robot Localization Using a Single Image." Proceedings of IEEE International Conference on Robotics and Automation, Sacramento, CA, April 9-11, pp. 978- 983.
11. Betke, M and Gurvits, L., 1994, "Mobile Robot Localization Using Landmarks." 1994 International Conference on Intelligent Robots and Systems (IROS'94). Munich, Germany, Sept. 12-16, pp.135-142.
12. Hager, G. and Atiya, S., 1993, "Real-Time Vision-Based Robot Localization." IEEE Transaction on Robotics and Automation, vol. 9, no. 6, pp. 785-800.
13. Fennema, C., Hanson, A., Riseman, E., Beveridge, J.R., and Kumar, R., 1990, "Model-Directed Mobile Robot Navigation." IEEE Transactions on Systems, Man, and Cybernetics, vol 20, no 6, November, pp. 1352-1369.
14. Kak, A., Andress, K., Lopez-Abadia, and Carroll, M., 1990, "Hierarchical Evidence Accumulation in the PSEIKI System and Experiments in Model-driven Mobile Robot Navigation." in Uncertainty in Artificial Intelligence, Vol. 5, Elsevier Science Publishers B. V., North-Holland, pp. 353-369.
15. Talluri, R., and Aggarwal, J., 1993, "Position Estimation Techniques for an Autonomous Mobile Robot - a Review." in Handbook of Pattern Recognition and Computer Vision, World Scientific: Singapore, Chapter 4.4, pp. 769-801.
16. Moravec, H.P., 1981, "Robot Rover Visual Navigation." UMI Research Press, Ann Arbor, Michigan.
17. Matthies, L. and Shafer, S.A., 1987, "Error Handling in Stereo Navigation." IEEE Transaction on Robotics and Automation, vol. 3, pp. 239-248.
18. Ayache N. and Faugeras, O.D., 1987, "Building a Consistent 3-D Representation of a Mobile Robot Environment by Combining Multiple Stereo Views." Proc. Internaltional Joint Conference on Aritificial Intelligence, pp. 808-810.
19. Joblove, G.H.and D. Greenberg, "Color spaces for computer graphics", Computer graphics 12,3, Agosto 1978, 20-25.
20. S.Yalamanchili, W.N. Martin, J.K.Aggarwal, "Extraction of moving object description via differencing", Computer Graphics and Image Proc., Vol.18, pp.188-201,1982.