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Gipsy: Knowledge Based Surface Inspection

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Abstract

Despite of a great demand of automatic image analysis systems in the production industry, the spread of installed systems is still limited. Reasons for this are, among others, the high requirements of image analysis systems with respect to computational effort and accuracy, the high engineering effort for the development of image analysis applications, and thus high investment costs for image analysis systems. Another problem, which frequently occurs, is the lack of samples for the adaptation of classificators, which leads to unstable classificators.

This paper describes the concept for a generic inspection system which follows the goals fast processing speed, stable and accurate classification, and low development effort. Essential points are the concept of „Abstract Sensors“ and the integration of numerical adaptation and explicit knowledge about the task domain and the inspection system. The modular structure of the system allows easy adaptation to new image analysis applications.

1. Introduction

Despite of a great demand of automatic image analysis systems in the production industry, the spread of installed systems is still limited. According to the german Vision Club, only about 5% of those tasks, which could be solved by industrial inspection systems, are carried out by such systems [8]. Reasons for this are among others:

1. The high processing speed denies the execution of sophisticated operators, which are necessary to solve complex problems.
2. The adaptation of existing procedures to concrete tasks need very high engineering effort, which produces high investment costs.
3. Later adaptation of already installed systems to altered tasks can be carried out only by specialists. The costs for such adaptations are therefore considerable.
4. Unsharp discrimination criterias between the different classes and unclear and contradicting names and descriptions of object and defect classes make the design of suitable classificators difficult.
5. In most cases, the available training set to adapt a system is too small.

Various attempts on several levels have been made in the past to overcome these problems:

1. Special hardware components have been developed to speed up expendable algorithms. However, special hardware is less flexible and needs higher development effort compared to software solutions.
2. In order to accelerate the process of development of new image processing systems for special applications researchers have worked on systems for automatic generation of operator paths and automatic justification of operator parameters (e.g. [3], [6]). These researches, however, do not or not sufficiently consider the special requirements of industrial image processing because of their general character. Furthermore, the knowledge acquisition problem is still vague for these systems.

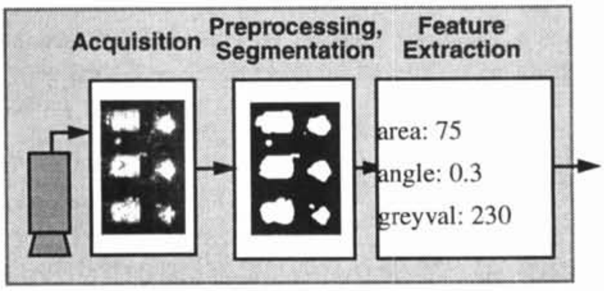
The next sections describe and discuss a concept for a generic knowledge based inspection system, which addresses the special requirements of image processing systems in industrial production environments.

2. System Structure

The design of the system structure of GIPSY follows the following main goals:

- stable and accurate classification,
- low development effort to adapt the system to a new application,
- fast processing speed to meet the realtime requirements of industrial processes.

Figure 1. Structure of an Abstract Sensor



In order to reach these goals the concept of „Abstract Sensors“ is used. A sensor in GIPSY is defined as the path from the acquisition data through preprocessing operators and segmentation up to the computation of object features (Figure 1).

Since the sensors consist of predefined and hardlinked operator paths with only few free parameters, execution of a sensor is typically fast. The necessary flexibility of the system at run-time is gained through many parallel sensors, while every sensor fulfils a specific task.

Sensors are called Abstract Sensors because several Abstract Sensors may share the same operators or physical sensors such as cameras. This way, double execution of operators on the same data is avoided.

From outside the Abstract Sensors every Abstract Sensor is looked upon as a unique block. This facilitates the control of the Abstract Sensors by the second main block of GIPSY: the knowledge based evaluation.

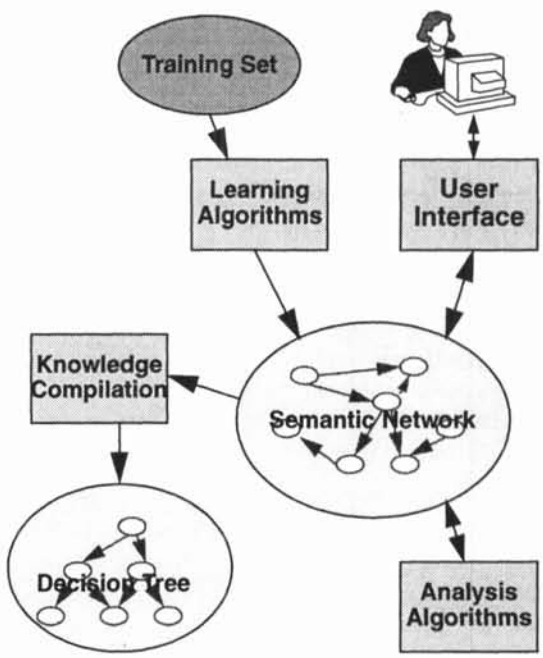
The knowledge based evaluation consists of two parallel parts, a knowledge based diagnosis system with a flexible inference machine using semantic networks, and a hierarchical classificator or decision tree. The decision tree contains all information necessary to fulfil the task of recognizing objects or defects at run-time. The representation of the knowledge in a decision tree allows a fast classification but is less flexible than the representation in a semantic network. Thus, during the design of the classificator, the representation in the semantic network is used, which facilitates the comprehension of the decisions made by the system.

3. Classificator Design

The core of GIPSY is the knowledge based evaluation of the results obtained by the Abstract Sensors. The main problems during classificator design are unsharp discrimination criterias and small sample sets. Although the intra observer error and the inter observer error during classification of objects or defects by human observers are considerable ([4]), humans are in many cases able to fulfil a classification task in a satisfactory manner. An image processing system, that has to decide e.g. whether a region is a certain defect or not, needs information about the model of this defect with respect to features computed by the Abstract Sensors. However, the coherence between the feature values and defect or object classes is not explicitly known. There are two possibilities to make the coherence explicitly known: formulating explicit classification rules, which means to extract the implicit knowledge out of the application expert, and the adaptation of classificators by means of training sets.

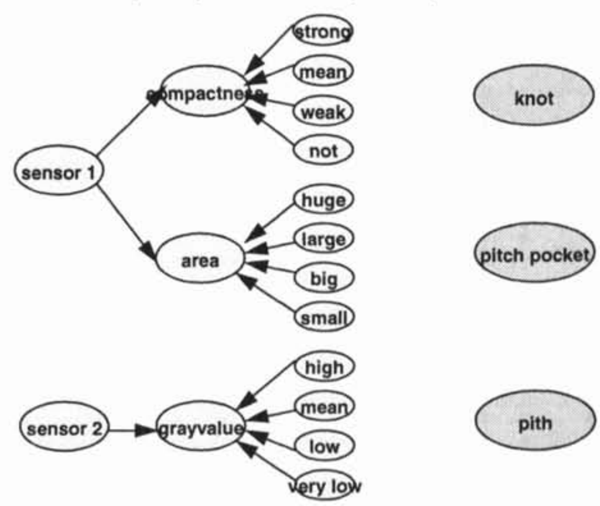
To adapt a classificator using a training set, however, a proper training set is necessary. In many cases, the training set is not large enough, it does not span the entire feature space or there are no examples at all for some classes. This means, that it is impossible to adapt a classificator using the training set alone. The application expert, who does visual inspection himself, has the necessary knowledge, but is unable to express this knowledge.

Figure 2. Building classificators with GIPSY



Much research has been done in the past years to ease knowledge acquisition (e.g. [2], [7]). The approach of GIPSY is to combine the information contained in those samples, which are available, and the implicit knowledge from the application expert. The knowledge based block of GIPSY consists of two main parts to fulfil this task: a set of learning algorithms to build a semantic network out of data from a sample set, and a graphical user interface to visualize the semantic network (Figure 2).

Figure 3. First network after definition of object classes (example: wood inspection)



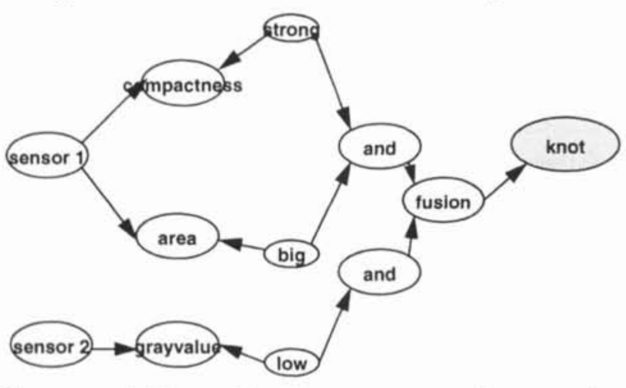
The classificator design starts by the definition of object or defect classes by the user. The system itself knows about the available Abstract Sensors and the features they are computing. The feature values are represented as nodes of the semantic network. Since feature values in most cases are continuous, they have to be quantized before they can be represented as nodes. The quantization is currently done by simple thresholding. Today we use four quantization steps representing the levels *Not*, *Weak*, *Mean* and *Strong* (e.g. the compactness of an object is *Weak*). The quantization into four levels proved to be suitable in previous research work [3] to describe image or object features with symbols (Figure 3).

There are two methods to select a threshold: by knowledge about the feature and the objects, or by analysing a training set.

After the object or defect classes have been defined by the user the next step is to create a first network out of the information contained in the available sample set. The first step just collects all examples from the training set, instantiates the necessary primitive nodes (e.g. area: big and compactness: strong) and links the primitive nodes to the goal node (e.g. knot). Since there may be many examples of a goal node in the training set, for every example an intermediate node is inserted between the goal node and the primitive nodes, which can be looked upon as an and-node.

After the first learning step the semantic network consists of many examples of goal nodes. Each of them is linked via an and node to those primitive nodes, which can be instantiated for this goal node.

Figure 4. Semantic network of one example defect



Since several Abstract Sensors may generate instances for one and the same object or defect in the scene, the network may contain many and-nodes for one object or defect class. In the next step these and nodes are linked to a new node, which is inserted between the and-nodes and the goal node (Figure 4). This new node is responsible for the fusion of the signals of several sensors.

The next step is a simple analysis whether there are duplicate nodes in the network. If two or more examples of a goal node have the same structure, they are removed from the network. This is done to reduce the complexity of the network.

After this first initialization of the semantic network using training examples the user starts the browser and loads the network. The browser allows interactive manipulation of the network such as creating and deleting nodes and edges as well as manipulation of views of the network. Such, the user is able to visualize those parts of the network necessary to interpret and understand the information contained in these parts. He can then select examples from a test set and start an inference algorithm on those examples. The inference algorithm instantiates the necessary nodes of the network and displays the instances on the browser. The state of the instances (Confirmed, Unknown, Rejected) is displayed using different colours, so that the user is able to see at a glance which instance is confirmed and which is not.

If the inference algorithm produces the wrong result (the wrong goal node is instantiated), the user can follow the links from this wrong result back to the primitive nodes to find out at which point the wrong decision was made. He may then choose to remove or change links or he may justify some thresholds.

The last step in classificator design is the automatic generation of a decision tree out of the semantic network. This decision tree contains all information necessary to perform the classification at run-time and has the advantage of higher execution speed.

4. Results and Discussion

GIPSY is currently used in tests with two visual inspection systems. One of the applications concerns visual inspection of wood surfaces. The inspection system uses eight Abstract Sensors. Each of them computes 17 features. The inspection system has to discriminate between 15 different wood defect classes. The second application concerns visual inspection of chipboards.

Especially in these applications with visual inspection of natural material, GIPSY helps to reduce the complexity of the task. A high variance of the defects of a single class and many similar looking defect classes make the design of a classificator extremely difficult. The semantic net browser of GIPSY together with the learning and analysis modules help to understand the structural appearance of wood defects with respect to their pictorial representation.

Current work focuses on the integration of concepts from fuzzy logic to allow certainty measures and the development of learning algorithms for further extension and enhancements of the network after the first learning steps.

5. Conclusion

The generic inspection system GIPSY has the following advantages over classical approaches to design industrial inspection systems:

1. **Robustness**:
   The application of explicit knowledge representation in GIPSY enhances the robustness of the system. One reason for this is that the core algorithms in GIPSY are used in a great number of applications. Since every application is tested and debugged, the core of GIPSY becomes more and more stable. Furthermore, the explicit knowledge representation together with intelligent user interfaces allows to understand the mode of operation of the system by the user and thus leads to better classification criterias.
2. **Efficiency**:
   GIPSY is able to use expendable algorithms and simultaneously fulfil the realtime requirements of the application. This is attained by executing expendable algorithms only in those cases, where they are really needed for the diagnosis.
3. **Easy adaptation to new applications**:
   The generic approach quickens the design of new or altered inspection systems by adaptation of the classificator. Only few application specific Abstract Sensors have to be implemented. Every Abstract Sensor, once designed, may be used in other applications. Thus, GIPSY reduces the costs of inspection system design.

6. Acknowledgement

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