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AI-READY AUTOMATED VISUAL INSPECTION: CONCEPTUALIZATION AND DEVELOPMENT OF A NEURO-FUZZY SYSTEM

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Abstract

An appealing option for businesses looking to save costs on component inspection is automated visual inspection (AVI). Camera systems for component inspection allow for less manual work and maybe better output rates. For the automobile sector, where product lifespans are often short and where suppliers are under growing pressure to provide flawless components, this is of paramount importance. However, setting up an AVI system may be complicated, particularly for businesses that have little expertise with vision systems. This causes training periods to be lengthy and the advantages to be under-realized. The goal of the work presented in this thesis is to create and build an image-processing algorithm that may aid in shortening the required training period and adjusting for external factors, such as surface lighting, that can affect the accuracy of the results. The software is able to learn the inspection process from samples of excellent and poor components thanks to the use of "intelligent" algorithms (particularly neural networks and fuzzy logic). The user is not only giving the data necessary to generate an accurate classification, but also, indirectly, the predicted variance in the photographs via the provision of sample images. This implies that the intelligent algorithm does not need being informed the maximum permissible variance, in contrast to more conventional systems. The algorithm was put through its paces using data from a customer in the industrial sector as well as photographs created in the lab. Results indicate that training times may be drastically reduced by switching to an example-based method. Classification performance was found to be on par with that of conventional threshold-based methods for pictures with a clear pass/fail distinction. The neuro-fuzzy system somewhat outperforms other methods when dealing with small discrepancies. In order to implement and test in an industrial setting, a user interface was designed.

Introduction

The strain on manufacturers to satisfy a wide variety of customer needs is increasing. Due to the complexity of the manufacturing industry today, fundamental requirements like inspection and quality control are frequently disregarded as potential areas for research and increased efficiency. Rising inspection prices may be attributed to the "zero defect" policies adopted by the car industry (Luke, 2000). Costs are on the rise, but they might be mitigated with better automated inspection methods. The focus of this study is on using intelligent (neuro-fuzzy) technologies to enhance the quality of the manufacturing process's components inspection phase. Currently, five Canadian institutions are working on developing this system at the same time. Each institution has researchers investigating issues related to industrial inspection from

Overview of the Issue

AVI systems have been used in factories for decades. The adaptability of these systems is

appealing since it allows for several uses of the same hardware. Another perk is that operators may rest easy knowing that the technology they're using operates on the same data that people do: visible light. Nonetheless, it's easy to lose sight of the fact that the human visual system is very intricate. The inspection duties that come naturally to people might be challenging for a computer system. Because of the nature of the assembly area at a factory, the situation is considerably more dire there. Light, smoke, dust, and other contaminants may easily enter the inspection area since the process is not isolated from the rest of the facility. Although

While the human visual system is able to immediately adjust to these variations, they may nevertheless make a well-tuned AVI system ineffective. Weaknesses in vision systems originate from their over-reliance on predefined thresholds for analysis. Because the output abruptly shifts anytime the input reaches a fixed threshold, they are quickly disturbed by changes in the surroundings. The incident at Van Rob Stampings is an excellent real-world illustration of this category of issues. They make metal stampings for cars. In order to build a single dashboard mount, 46 metal clips are put into the beam to provide threads for the fasteners (see Figure 1.1). During different points in the procedure, the clips are inserted both manually and using automated machinery. All of the beams are inspected for completeness and accuracy before moving on to the next stage.

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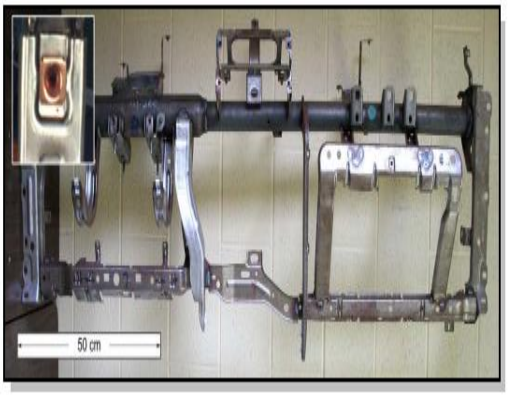

Fig 1An Analysis of the Existing Literature

Performing a Quality Check

In order to ensure that the final product is both functional and aesthetically pleasing, quality control measures are used throughout production. Maintaining a high standard of quality may be accomplished in part via regular quality inspections. Some or all components may be examined, depending on manufacturing speeds and inspection complexity. The findings of a sample inspection are analysed statistically to infer the status of the whole. In most cases, a thorough examination is recommended over a statistical extrapolation to establish the quality of the components as a whole. In contrast, complete inspection is only practical if the components are manufactured slowly enough, have few inspection requirements, or are amenable to automated inspection techniques. Very low rates of output are unusual for a variety of reasons, and this is because they are often considered to be undesirable. Similarly, straightforward inspection is seldom preferred since additional problems may be discovered, categorized, and addressed by altering the inspection process itself.

Thus, many businesses are turning to automated inspection systems to boost output and cut down on waste (Thomas, 2006). The majority of inspection needs may be broken down into the following three classes: component location, dimensional analysis, and surface condition (Hunter, 1995). Parts assembly verification relies on checking for the presence and correct orientation of all necessary components, which is what "part location" does. A dimensional analysis is performed to check the dimensions of each part and feature to guarantee accurate manufacturing. Taking a look at the surface's condition is a certain way to make that the surface's finish meets standards and that no damage occurred during production. A broad range of approaches have been developed to automate these procedures. Semi-automated methods use apparatus and/or software to aid a human inspector in taking precise measurements and documenting the findings (see Figure 2.1). These tools relieve the operator of significant mental labour but still need human muscle. Because of this, any money saved by switching to an automated method is wasted.

As shown in Figure 2semi-automated inspection devices help human operators by keeping tabs on their tools to make sure they've finished what they need to at a given assembly station (Wilson, 2006).

Similarly, coordinate measurement machines (CMMs) are a kind of semi-automated inspection that examine a part by contacting a probe to strategic reference locations on the part (see Figure 2.2). The inspection procedure is time-consuming and must be performed in clean, quiet environments apart from the assembly area's noise and commotion. As a result, it is usually reserved for a select number of components or for situations calling for an exceptionally high degree of accuracy.

Coordinate measurement machine, as shown in Figure 2.3

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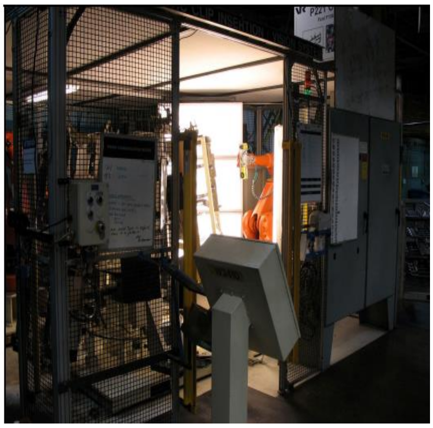
(Brown & Sharpe, 2007) It is preferable to prevent mechanical contact with the components in order to achieve high speeds and limit the number of bespoke tools needed for inspection. As the need for more adaptable techniques increases, automated visual inspection (AVI) has emerged as a viable option. One component of an AVI system is a camera that takes pictures of the component. The data is then processed by a computer to extract the important characteristics of the item and verify the quality of the manufacturing. In Figure 2.3, we see an example of an AVI system used in an industrial setting.



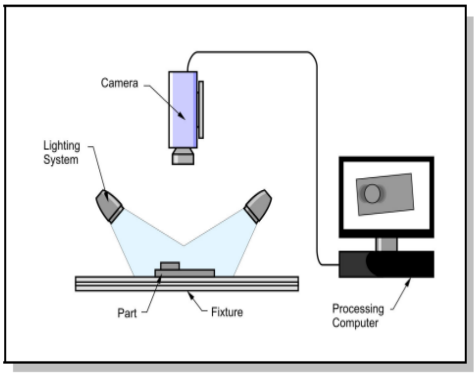
Here at Van Rob Stampings, we have an Automated Visual Inspection system (see Figure 2.4) that does a great job of keeping our quality high. The robot has two cameras installed on it, and the operator may see the feed from within the cage on a console (foreground).

Inspected Mechanically and Mechanically Inspected Automatically

For a long time, people relied only on visual examination when checking the quality of components. Surface flaws, improper construction, and physical damage to the component may all be revealed by observing its outward appearance. Automatic visual inspection (AVI) systems aim to utilize this visual data to do the examination without human involvement. In a perfect world, the inspection space wouldn't need to be modified at all so that AVI systems could perform as well as a human inspector.

However, the human visual system is highly complicated, and a simple activity to a person may take an automated system months to train for.

The manufacturing industry is home to a diverse range of environments, therefore AVI systems come in a wide number of shapes, sizes, and configurations to best suit the task at hand. But as can be seen in Figure 2.4, the core of almost every system consists of a camera, a lighting system, and a processing device of some kind. These days, it's not uncommon to see a single device that performs many of these roles.



The main parts of an AVI system are shown in Figure 2.5

Figure 2.5 and the following text break down the four primary steps involved in capturing the part's look and then processing it to get a final accept/reject judgment.

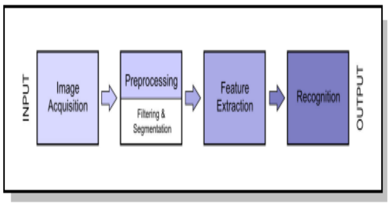


Figure.5: Steps in the AVI process

Camera Configuration

Physical and software adjustments must be made to the camera in order to capture a picture with the highest resolution and most relevant details.

Decide On a Lens

Lenses are more important than the quantity of pixels on a camera's sensor when it comes to defining what parts of an image each pixel captures. The camera's field of view cannot be adjusted due to the lack of a zoom feature in most machine vision lenses. The system's advantages include the fact that, at any given distance from the camera, the size of any given item in the frame will stay constant. Thus, distances in the actual world

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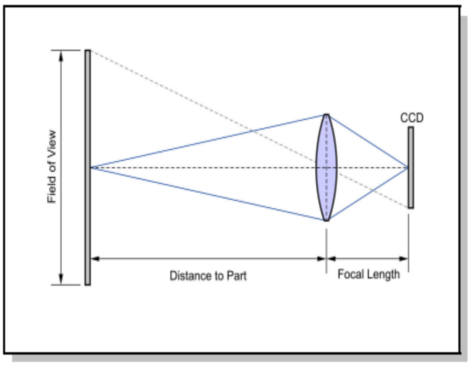
may be estimated based on the number of pixels an item occupies in a picture.

Given that the viewing angle is fixed, the focal length must be chosen to provide the required field of vision at the part's working distance. As the camera's location is also a factor, the same field of vision may be achieved via a variety of focal length/camera distance combinations (see Figure 2.6).



The geometry of a basic camera lens system is seen in Figure 6.

The impact of perspective is mitigated, however, when the camera is placed at a greater distance from the subject. This means that parallel lines on the component will seem even more parallel. Using a wide-angle lens on a camera that is extremely near to the action may cause visual distortion. On the other side, the more distant the camera is from the component, the more opportunities there are for blur due to camera mount vibration or for haze to form from airborne particles. So, it's important to strike a balance between distance and distortion that works well for the intended purpose.

Methods of Image Processing

Pixel values are the fundamental building blocks for all image calculations since practically all pictures on computers are recorded in this way. The picture may be interpreted in several ways.

Pixel-Based

Working with the raw pixel data is the simplest kind of processing. Fast to calculate and often providing all the necessary data, image attributes including average intensity, ratio of dark to bright pixels, intensity deviation, color histogram, and similar global metrics are common. The intensity and color of a single pixel, however, are frequently unrelated to the actual content of the picture. One obvious scenario in which this occurs is when the component moves with respect to the camera and is no longer captured by the same group of pixels.

Methods for Extracting Features

By definition, feature extraction encompasses any procedure performed on an image that yields more information about the picture. It might be the location of lines, the number of pixels that meet some criterion, or statistical statistics like the mean and standard deviation for each row and column. What kind of feature description is employed is largely context dependent. The objective is to provide the most informative data possible, which will serve to emphasize the target. In this part, we'll look at how to extract high-level features, such as lines, circles, and color. These characteristics have the benefit of being easy to understand for the user, but they aren't necessarily the greatest descriptors for doing picture analysis.

Ways of Locating Margins

Finding the boundaries of a picture is the first step in discovering the forms inside it. In the field of image processing, an edge is defined as a region where there is a sharp transition in pixel brightness. The angle between the reflecting surface and the camera has a major impact on the amount of light that is reflected. Therefore, the borders of the section, where two faces with different angles meet, are often where there is a drastic variation in pixel intensity. Undoubtedly, theresurface printing (text, images, etc.), shadows, and highlights are some more examples of things that might cause an edge to be falsely detected. Making a gradient map is a quick and easy method for finding edges. Values for each pixel in this picture reflect the degree of gradient contained in the source image. This is how we determine the size of the gradient:

$$G_x = \frac{\partial f}{\partial x}, G_y = \frac{\partial f}{\partial y}, |G| = \sqrt{G_x^{\,2} + G_y^{\,2}}$$

x, y are picture coordinates and f are the intensity there (Gonzalez et al., 2004). The strength of the x and y components may also be used to figure out the edge's orientation. One way to find potential edge spots is to analyse an image's gradient values. All gradient values over a certain threshold are considered to be edges. In contrast, some strategies begin their hunt at the gradient's apexes and work their way out along the edges in a continuous fashion. Canny edge detection is one such common approach (Gonzalez et al., 2004). The results of applying the Canny edge detector to a picture are shown in Figure 2.9.

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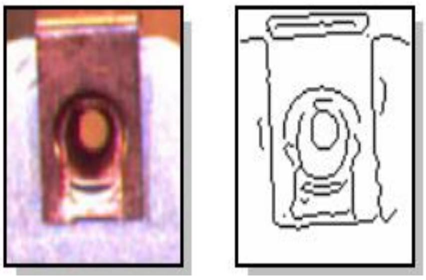
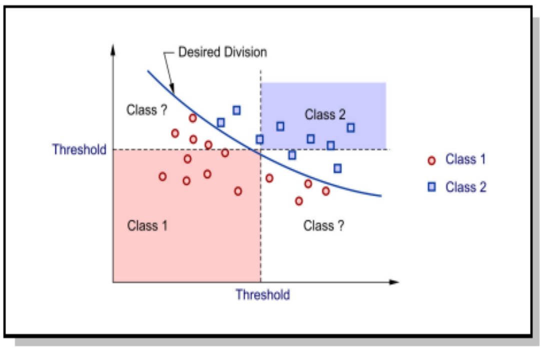


Fig 7. a classification method's job is to segment the input space along the dimension you've chosen. Output of the Canny edge detector (right) applied to a J-clip picture (left) (left).

Classification Based on Thresholds

During the recognition phase of quality inspection, a component is often just given a basic pass or fail classification. Space is partitioned into n-dimensional areas that signify the borders of pass and fail zones if the retrieved image features have n characteristics each. The range of input values is then used to categorize the values into groups. Conventional AVI systems use a fixed threshold approach, in which feature values are compared to limitations established explicitly by the user during the system's configuration. If a threshold test fails on any one dimension, the whole component will fail. When ensuring dimensions are within a certain range for compatibility with other assemblies, this method is often used. In certain cases, Threshold won't be able to provide enough stratification. If there are just two inputs, the resulting space is flat, and the threshold may be used to partition it into rectangular cells. While threshold-based categorization works well for straight lines, it fails miserably if the genuine divide follows an inclined or curved border (see Figure 2.15). The same applies to input spaces of any dimension.

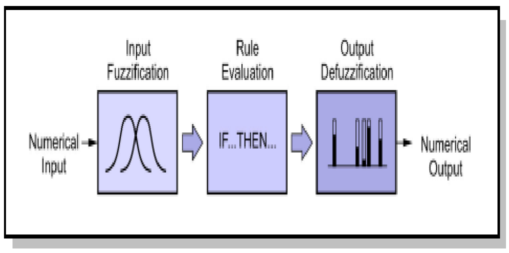


Perpendicular borders may not accurately reflect the intended class division when the input space is partitioned using threshold values for each dimension, as shown in Figure 8.

Taking into account each dimension separately is a step beyond the standard threshold method. Once the category for each input dimension has been established, the results are aggregated to get a final verdict. This implies that a decision may be made based on the majority's findings even if one characteristic is absent or inadequately retrieved. It may be as easy as averaging or mediating the inputs to get the final categories.

Identifying and Sorting Data using Fuzzy Logic

The idea of using human knowledge to teach computers led to the development of fuzzy logic. It is challenging to translate the expertise of a person to a computer-processable equation when there are many variables and circumstances involved in the process. Fuzzy logic is able to provide a smooth output surface for all input combinations without an explicit explanation of the process because it encodes human experience as a sequence of IF-THEN rules (Nguyen and Walker, 2006). As may be seen in Figure 2.16 and elaborated upon below, fuzzy inference systems consist of three distinct phases: input fuzzification, rule evaluation, and output defuzzification.



The steps of a fuzzy inference system are shown in Figure 9.

Assumption Fuzzification of Input A key step in the input fuzzification process is the transformation of the original crisp values (numerical input values) into linguistic variables. Labels like "HOT" and "COLD" are examples of linguistic variables; they reflect how a person would characterize the value. It is the membership functions that determine the mapping from input values to the linguistic variables, and these functions are unique for each input. Overlapping is allowed between membership functions, which are commonly trapezoidal, triangular, or Gaussian in form. For each given input dimension, the membership functions are discrete subsets of the whole fuzzy set. Fuzzy sets,

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in contrast to more conventional crisp sets, let data points to be both non-complete and multiple-member subsets. An input value's degree of connection may range from 0 (no association) to 1 (strong association), indicating the extent to which that value is part of a certain subset (complete association).

An example is the greatest way to demonstrate the idea of fuzzy sets. Picture a situation where temperatures must be categorized. A clean method would be to create two

categorizations: HOT and COLD. If the 20°C line in Figure 2.15 were the dividing line between these two groups, then temperatures of 19.9°C would be classified as COLD and those of 20.1°C as HOT. Since there is a middle ground about 20 degrees Celsius where the temperature would be either "a touch chilly" or "not very hot," this does not mesh well with the way humans perceive heat and cold.

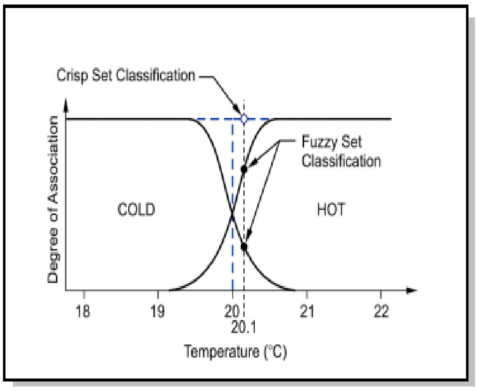

Figure 11. illustrates a case in which the distinction between crisp and fuzzy sets is useful. When the temperature reaches 20 degrees Celsius, the crisp set abruptly changes its categorization, while the fuzzy set allows for a more gradual transition.

Temperatures close to 20 degrees Celsius would be somewhat associated with both the HOT and COLD subsets, which may be captured by a fuzzy logic set with overlapping membership functions that slant to the sides. According to the membership functions shown in Figure 2.17, if the temperature were 20.1 degrees Celsius, it would be most closely associated with the HOT group (by a factor of approximately 0.7) and least closely associated with the COLD group (by a factor of about 0.3).

Testing The Rules As soon as the inputs are fuzzified into linguistic variables, they may be utilized to test rules without needing to directly reference the original numerical values. A rule's fundamental framework is shown in Figure 2.18 as an IF, THEN statement.

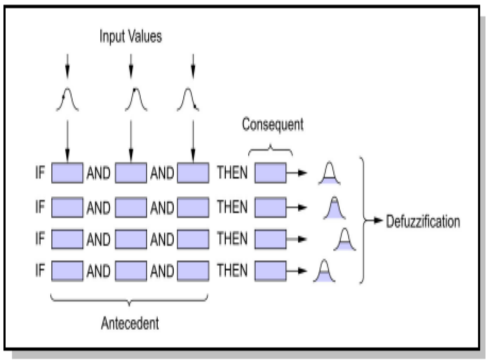

Fig 12 Diagrammatic representation of the organization of fuzzy rules and their connection to the rest of the fuzzy system. The antecedent of the rule is a set of language variables that have been "fuzzed" from the inputs. Each subsequent part's output is calculated using the input from its predecessor.

Sticking with the topic of heat, a rule may go something like this:

The first component of the rule, IF (T is COLD AND (T is NEGATIVE) THEN (Heater Power is HIGH), is called the antecedent. For the antecedent, we use a union operator like AND or OR to unite terms that relate to the input linguistic variables (which are determined by the input membership functions). Rule evaluation is performed by ANDing or Oaring the degrees of connection of each antecedent variable. However, AND and OR evaluations are limited to binary input variables (logical one or zero). Given that the value of the degree of linkage

non-discrete, a variety of AND/OR operator options have been devised (see Table 2.1 for some examples).

This table 2.1 shows some examples of AND and OR operators that may be used with continuous variables (A(x), B(x)). All MATLAB® users should be familiar with these four operations (Kerman, 2001).

AND	OR
Minimum $MIN(\mu_A(x), \mu_B(x))$	Maximum $MAX(\mu_A(x), \mu_B(x))$
Algebraic Product $\mu_A(x)\mu_B(x)$	Algebraic Sum $\mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x)$

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Rule efficacy is equal to the sum of the values of preceding associations' degrees of significance. In this case, the intensity of the shot might be used as a proxy for how effectively the rule was followed. The right side of an expression (the consequent) should have a major impact on the output if the rule is fired aggressively. The rule's consequence refers to language-specific output variables. Input-style membership functions or simple scalars may both be used to represent these variables (called singletons). In the defuzzification procedure, the rule's firing strength is employed to provide a weight to the resulting output.

Resolution of Ambiguity at the Output

Defuzzification works to standardize the network's output by summing the results of each rule's application. For the regulations to be effective, their results must be

membership functions, and then the region beneath the membership function is shortened based on the rule's firing strength. The output value is obtained by adding the regions determined by each rule and then selecting the centroid (see Figure 2.19). The genuine centroid computation in the center of area calculation may be simplified into approximations for speedier processing.

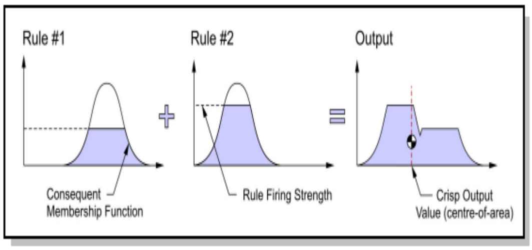
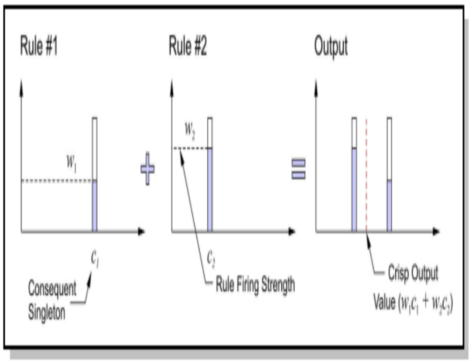


Figure 13: The process by which the rule consequent membership functions are combined to calculate a single crisp output for the network.

For the case of singleton consequents, the calculation is simply a weighted average of each singleton where the weights are the firing strengths of the rules (see Figure 2.20). This calculation is much less computationally expensive than the area centroid method so singleton outputs are preferred where speed is an issue.



As can be seen in Fig. 14 when singleton outputs are defuzzied, the resulting value is only a weighted average of the original values.

Fuzzy logic systems may provide a continuous, smooth output even when presented with inputs that do not match those used in the training set by resorting to centroid or weighted average computations. This mimics the way humans might extrapolate knowledge from known sources and generate opinions about previously unknown circumstances.

CONCLUSIONS

that there is no longer a problem with this. Testing with more difficult photos than those already in the databases is an excellent place to start. Images with numerous clip positions, poor illumination, or blurriness are examples of such examples. Van Rob has said that Queen's University may have access to this sort of picture collection for future research. Incorporating example-based training into a pre-existing AVI system is another viable option for widespread industrial use. Such a solution would broaden the method's appeal while retaining many of the neuro-fuzzy system's benefits (easy training, automatic optimization of feature attributes, automatic threshold setting). Then, after the users have a firm grasp on the algorithm's reasoning, they may roll out the whole neuro-fuzzy system in situations where it would be useful. Ultimately, the system will be evaluated based on how well it functions in a real-world production setting over a significant length of time. Simulating it is challenging since the difficulties that develop are seldom ones that have been encountered before. The testing results have revealed that this method has the ability to address some of the most widespread problems with existing AVI implementations.

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