INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH & DEVELOPMENT

ISSN 2278 – 0211 (Online)

An Adaptive ISS for Object Detection in Dynamic Backgrounds Using Neural Fuzzy Logic

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Abstract:
The key to surveillance systems is object detection. Many approaches to this task have been implemented over multiple decades, but still lag efficient performance in dynamic backgrounds. Systems developed so far requires complex computations and human beings intervention for parameter adjustments. The proposed method is based on a neural-fuzzy model. The neural stage, based on a one-to-one self-organizing map (SOM) architecture, deals with the dynamic background for object detection as well as shadow elimination. The fuzzy inference mamdani system mimics human behavior to automatically adjust the main parameters involved in the SOM detection model, making the system independent of the scenario. The model developed provides robustness over real video scenes.

1. Introduction

Surveillance is the monitoring of the behaviour, activities, or other changing information, usually of people for the purpose of influencing, managing, directing, or protecting them. Surveillance is very useful to governments and law enforcement to maintain social control, recognize and monitor threats, and prevent/investigate criminal activity. It is also used for driver's condition analysis, industrial applications, and marketing purposes. Furthermore, it is even used in child care applications. Surveillance cameras are video cameras used for the purpose of observing an area. They are often connected to a recording device or IP network, and may be watched by a security guard or law enforcement officer. Cameras and recording equipment used to be relatively expensive and required human personnel to monitor camera footage. Although vision cameras are being used everyday in new locations in our cities, the video analysis task is the responsibility of humans in many cases. Therefore, the benefits of the video information provided by the vision cameras are still limited to human performance. Unfortunately, it is known that only one–four screens can be really monitored at a time. Thus, a system with 100 cameras and 3 operators can only utilize 3% of screens. This situation has led some research groups to work on intelligent surveillance systems (ISS).

One of the principal goals of an ISS is to decrease human video analysis to avoid tedious tasks. Many of the current surveillance systems lack a reasonable level of intelligence and this deficiency must be compensated by humans. That is, humans need to inspect the set of monitors to detect possible security violation situations. Incorporating human intelligence into the system is not the problem. The real issue presents itself when human factors like fatigue and/or boredom arise. For example, it is common to find surveillance systems where two or three persons have to monitor several screens for many hours. This scenario can result in a high degree of failure to recognize possible hazardous situations captured by the surveillance cameras. The solution to this problem has been set forth by researchers specializing in surveillance systems. The possible solutions include providing intelligence to the surveillance systems so they can detect situations like abandoned objects, abnormal behaviours and restricted areas violation.

The proposed method is based on a neural-fuzzy model. The adaptive object detection method work in dynamic backgrounds without human intervention. The neural stage, based on a one-to-one self-organizing map (SOM) architecture, deals with the dynamic background for object detection as well as shadow elimination. The fuzzy inference mamdani system mimics human behaviour to automatically adjust the main parameters involved in the SOM detection model, making the system independent of the scenario. Results of the model over real video scenes show its robustness. Due to the promissory results on modeling adaptive dynamic systems using a computational approach, a simplified model of SOM-like dynamic background segmentation is used here. Its objective is to decrease the computational load by reducing the number of parameters that need to be tuned to improve background video segmentation. The reduced model will be able to deal with the detection of small moving objects, shadow reduction, and changing background conditions. It should also show the robustness in illumination changes. The proposed model also includes a fuzzy stage to automatically determine the parameter values required to process different video sequences without human intervention. The method also decreases the computational cost and preserves robustness in its performance. Through this proposed model the neural-fuzzy approach in this paper presents a good alternative for complete and automatic parameter determination in surveillance systems working with dynamic scenarios.

2. Existing Method

Different kinds of methods exist to solve the problem of motion detection and motion segmentation. One of them is background modelling and subtraction, which is a preliminary step to moving object detection and subsequent processing is necessary to get the masks of moving objects. First works were based on adjacent frames difference. However, this simple method is unsuitable for real world situations and statistical methods were introduced to model the background. Background modelling methods can be classified as predictive or non predictive methods. Non-predictive methods build a probability density function of the intensity at an individual pixel. Predictive methods use a dynamical model to predict the value of a pixel from previous observations. All these pixel-wise approaches allow an accurate detection of moving objects but are memory and possibly computationally expensive. Also, they can be sensitive to noise and they don't take into account spatial correlation. For these reasons, spatial consistency can be added as in modelling of both foreground and background is used to detect moving objects. This method has been extended to novelty detection . Feature based models also exist for background modelling. For example the background is modelled only on corners, and moving objects are then found by the clustering of foreground features trajectories. For numerous outdoor sequences, the changes in the background appear suddenly and, in case of gray scale videos, the objects may have intensity values close to the ones of the background. Hence, background modelling is difficult and often not sufficient.

2.1. Limitations

In the traditional methods of surveillance systems it faced many disadvantages like

- Occlusions and shadow elimination is difficult
- Modelling of stop zones is difficult
- False alarm is produced
- Computational parameters are more
- Human intervention during video segmentation
- Data redundancy and slow execution of algorithm

In this paper good alternative for complete and automatic parameter determination in surveillance systems working in dynamic scenarios can be developed. The colour space selected was the hue-saturation-value (HSV) model based on success in other literature. Literature indicates that using the HSV colour space discrimination of shadows can be performed. This is possible in this colour space because a shadow changes the background illumination significantly, whereas the colour or chromaticity only changes a little. The lighting, noise, reflections, and shadows of the videos involved should be considered to monitor different scenarios and thus problem of occlusion can be solved.

3. Proposed Method

Surveillance systems are closely related with two types of background modeling, namely static and dynamic. One of the objectives in the development of this model is that surveillance systems can be used more efficiently. Thus, they can be used not only by companies or institutions, but also by common people because of their low economic and computational costs. Hence, the concept of "everywhere-screening-eyes perspective" may be integrated into more complex systems. Background determination in video analysis is a paramount issue because by knowing this reference, other information of interest may be deduced from the video like dynamic objects or path patterns. Static background models are by far simpler and more efficient than dynamic background models; nevertheless, static models are limited to fewer possible applications than dynamic systems.

The proposed model is comprised of three stages: Initial background determination, dynamic background update, and dynamic background update optimization as shown in Fig.1. The model follows the basic idea of most background determining methods which define an initial or reference background for comparison purposes and later updated. This process reduces the false movement alarms due to illumination changes. The second stage of the segmentation method is the dynamic update. The dynamic actualization is achieved by a SOM-like architecture. In this model, each video color pixel $\mathbf{p}(x, y, t)$ is mapped into a SOM element $\boldsymbol{S}(x, y, t)$.

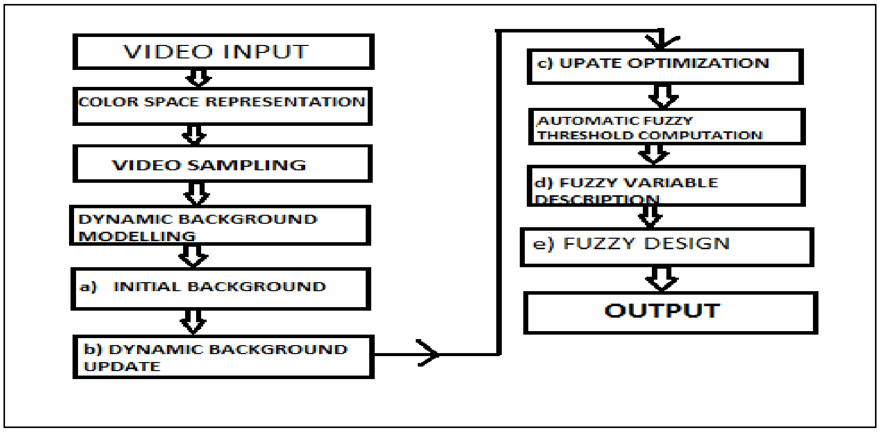

Figure 1: Flow chart of the proposed method including fuzzy logic

Video analysis has become a common task performed from information provided by cameras to deal with surveillance or security. Surveillance systems can be designed to work in static or dynamic backgrounds. Background determination in video analysis is a paramount issue because by knowing this reference, other information of interest may be deduced from the video like dynamic objects or path patterns. Static background models are by far simpler and more efficient than dynamic background models; nevertheless, static models are limited to fewer possible applications than dynamic systems. A video sequence is given as input of which nine frames are taken, as shown in Fig. 2.

The lighting, noise, reflections, and shadows of the videos involve the following conditions as shown in Fig.2. Frame 1 is an interior scenario with good illumination, no reflections, and a weak shadow. Frame 2 is similar to video 1. Frame 3 is an exterior scenario with good illumination conditions and no shadows or reflections. Frame 4 is an exterior scenario with very poor illumination conditions and no shadows or reflections and windy conditions. Frame 5 is an exterior scenario with good illumination, faint shadows, and no reflections. Frame 6 has regular illumination, and it involves shadows and reflections. Frame 7 is similar to Frame 6 but with less reflection. Frame 8 is an interior scenario with regular illumination, shadows, and reflections. Frame 9 is an interior scenario with good illumination in the center of the field of view and faint shadows and reflections.

Figure 2: Nine frames from a real time video is used in research

3.1. Initial Background

The model follows the basic idea of most background determining methods which define an initial or reference background for comparison purposes and later updated.

3.2. Dynamic Background Update

The dynamic actualization is achieved by a SOM-like architecture. Unsupervised training, in which the networks learn to form their own classifications of the training data without external help. In this model, each video color pixel $\mathbf{p}(x, y, t)$ is mapped into a SOM element $\boldsymbol{S}(x, y, t)$. There is evidence that SOM neural networks have been used satisfactorily for color segmentation and provide unsupervised characteristics; therefore, they yield an adequate representation of color and space coordinates. Unlike the model reported in, the method in this paper proposes a one to- one mapping between the pixels and the neuron elements. This reduces the computational load and the number of model parameters needed to tune. Another difference with common SOM architectures is that the stimuli input are fed individually. That is, each neuron is connected only to its corresponding pixel.

4. Automatic Fuzzy Threshold Computation Model

It is important to design an algorithm that automatically computes the required parameter values without human intervention, making the system independent of the scenario under analysis. In order to deal with this problem, a fuzzy logic approach is proposed. The fuzzy model developed for parameter determination is designed to incorporate the criteria of a human observer to define the values of *Th*1 and *Th*2. The fuzzy system computes these parameters every ten frames in order to maintain a consistent segmentation through the dynamic changes of illumination in the scenarios. The mamdani model is used here as in Fig.3

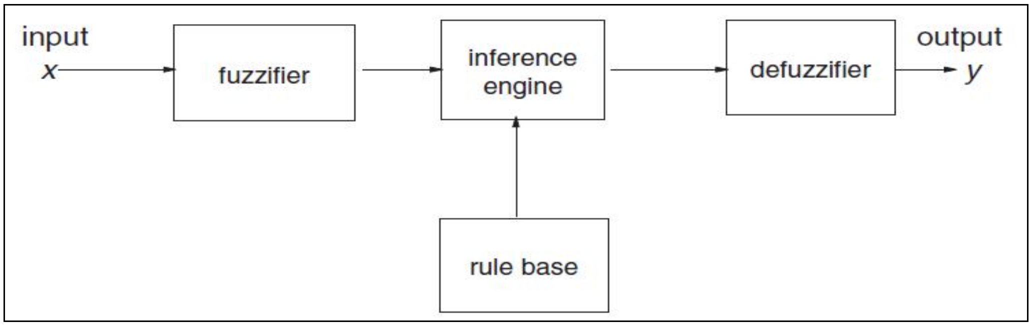

Figure 3: Block Diagram of a Fuzzy Inference System

A fuzzy inference system (FIS) essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, FL operators, fuzzy if–then rules, aggregation of output sets, and defuzzification. An FIS with multiple outputs can be considered as a collection of independent multi input, single-output systems. A general model of a fuzzy inference system (FIS) is shown in Fig. 3. Fuzzification is the process of making a crisp quantity fuzzy. This is done by simply recognizing that many of the quantities that are considered to be crisp and deterministic are actually not deterministic at all: They carry considerable uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably fuzzy and can be represented by a membership function. The FIS maps crisp inputs into crisp outputs. It can be seen from the figure that the FIS contains four components: the fuzzifier, inference engine, rule base, and defuzzifier. The rule base contains linguistic rules that are provided by experts. It is also possible to extract rules from numeric data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector. The fuzzifier maps input numbers into corresponding fuzzy memberships. This is required in order to activate rules that are in terms of linguistic variables. The fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets via membership functions. The inference engine defines mapping from input fuzzy sets into output fuzzy sets. It determines the degree to which the antecedent is satisfied for each rule. If the antecedent of a given rule has more than one clause, fuzzy operators are applied to obtain one number that represents the result of the antecedent for that rule. It is possible that one or more rules may fire at the same time. Outputs for all rules are then aggregated. During aggregation, fuzzy sets that represent the output of each rule are combined into a single fuzzy set. Fuzzy rules are fired in parallel, which is one of the important aspects of an FIS. In an FIS, the order in which rules are fired does not affect the output. The defuzzifier maps output fuzzy sets into a crisp number. Several methods for defuzzification are used in practice, including the centroid, maximum, mean of maxima, height, and modified height defuzzifier. The most popular defuzzification method is the centroid, which calculates and returns the center of gravity of the aggregated fuzzy set. The fuzzy systems consist of two inputs, illumination *V* and saturation *S*, as well as two outputs, *Th*1 and *Th*2.

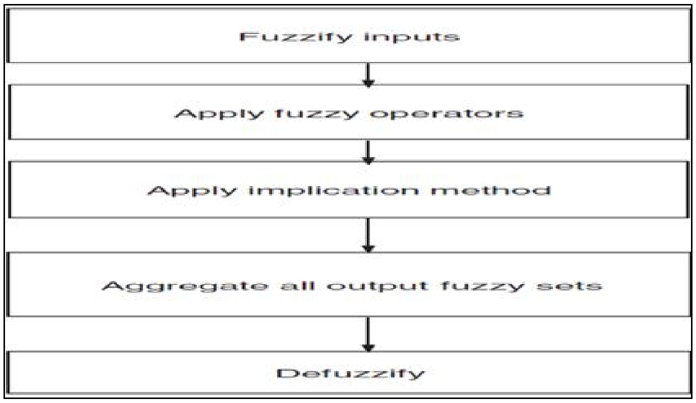

Figure 4: Fuzzy inference process

4.1. Fuzzy Rules Design

The rules for the Mamdani fuzzy system are described as follows.

- *R1*. **If** *S* is *Low* **AND** *V* is *low then Th*1 and *Th*2 are *low*.
- *R2*. **If** *S* is *Medium* **AND** *V* is *Medium* **Then** *Th*1 and *Th*2 are *Medium.*
- *R3*. **If** *S* is *high* **AND** *V* is *high* **Then** *Th*1 and *Th*2 are *high*.

The fuzzy outputs of the Mamdani systems are illustrated in Fig. 7.

5. Conclusion

An Adaptive ISS (Intelligent Surveillance System) for Object Detection which works with moving backgrounds and gradual illumination variations as well as other characteristics with an acceptable performance can be developed. This approach can be considered robust and intelligent because of its adaptive and dynamic behaviour. The computational load can be made simpler by reducing the number of parameters that need to be tuned to improve background video segmentation with the help of fuzzy stage. It Deals with small moving objects, shadow reduction, changing background conditions and illumination changes and efficiency of surveillance can be improved. This can be claimed as automatic model without any human intervention or previous training. The frames were selected such that they incorporate different conditions, positive and negative, as they can be used to compute a realistic evaluation of the proposed algorithm.

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