A video surveillance method based on information granularity

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Abstract – This article presents a surveillance system composed of video cameras. A localization is made using the information obtained from video cameras and the proper set of attributes is selected. An uncertainty measurement is performed based on the similarity with the nearest prototype and the dissimilarity from the rest of prototypes. The best granularity is also determined

***Index Terms* - Video surveillance, granularity, uncertainty measurement, dissimilarity.**

I. INTRODUCTION

Surveillance systems are used today on a large scale, mostly in indoor areas, but also in outdoor environments. For outdoor surveillance especially, video cameras are used because they can provide a large scale of information in a format close to human's most important sensor, namely the eye. For this reason, a wealth of papers related with surveillance based on video cameras exists. The major subjects encountered are segmentation [1], [10], tracking [3], [6], [11] and recognition [4], [5], [9].

This vast number of articles is also explained by the complexity of the captured images, and the numerous parameters that can influence the results. For two or more video cameras, there will be a three dimension variation in space coordinates, one variation in time dimensionality, one in brightness dimension and one in color variation, which leads to a vary large variability of information. Another fact that increases the complexity of the problem is that the image is obtained by reflecting the lights produced by different sources. They are then transmitted throw an optic medium to the captor, all this inducing noises and faulty information. From these facts it can be concluded that:

- the information obtained by the video sensors has a large range of uncertainty
- the surveillance efficiencies can be improved by using different types of sensors for observations of the same environment, reducing this way the variability of the searched space.

In this article, a surveillance system that takes into consideration these two observations will be presented. The two cameras permit a triangulation and the recognition of the features; afterwards, the corresponding granularity pattern and the degree of uncertainty are determined.

The material is organized into 3 sections. First, in Section II, the theoretical explanations for the procedure used in video systems are presented. Considerations on uncertainty measurements and on multi-attribute sets are then made. The way to establish the optimal granularity is also explained.. Section III presents the experiments that confirm the theoretical parts, and Conclusions are expressed in Section IV.

II. VIDEO SURVEILLANCE

A. Uncertainty measurement

The fuzzy similarity relationship proposed in [2] will be used. This relationship is obtained by overlaying two fuzzy relationships, that of inclusion and that of dominance. The first one implies a fuzzy implication relationship, and establishes the degree of inclusion of a variable x in an interval boarded by a constant value a. The second one implies the fuzzy implications between a boarded constant b and the variable x. Thus, the similarity relationship is:

$$sim(x,a,b) = (a \to x) \otimes (x \to b) \quad (1)$$

Thus, the label of the unknown feature is determined by the nearest prototype, which is also the most similar to it:

$$S(x,a,b) = \max(sim(x,a,b)) \quad (5)$$

The feature is also compared to the next nearest prototype. The dissimilarity is then determined from this reference point. Dissimilarity is considered the complementary measure of similarity, and its relationship is determined by using the negation of the latter one. In the present paper, the classical negation will be used. The resulting relationship for this measure is:

$$D(x,a,b)=\min_{i=1,N} \ (1\text{-}sim(y,a_i,b_i)) \quad (6)$$

From the relationship between these two measurements the measure of uncertainty, expressed as a difference between the similarity with the closest prototype and the dissimilarity from the second closest prototype can be determined:

$$U(x,a,b)=S(x,a,b)-D(x,a,b) \quad (7)$$

If the result of this measurement is positive, then small values indicate small uncertainty, because the labeled feature is similar to the designed prototype, and is weakly similar to the next closest one.

In the case of $U(x,a,b)>0$ being large, it can be concluded that uncertainty is important, because the difference of similarity between the feature and the next nearest prototypes is small, and the possibility of it belonging to each of these two classes is high, resulting that the probability of making a mistake is considerable.

If the difference has a negative value, it can be concluded that the feature does not belong to the investigated class, because it is more similar to another prototype, or it can be labeled on the information provided by the existent prototypes.

B. Granularity determination

By using an outdoor surveillance system, the distance of observation can vary in a large range. This means that different features depending on the observation distance that correspond to different granularities can characterize the same object. These features A_i are related not to an object, but to an observed structure of the observed object, depending on the granularity of the observation

$$St^n \rightarrow \{A_1,..A_i...A_n\} \quad (8)$$

Thus, an object with a hierarchical structure can have on a lower level a St^n structure, characterized by the attributes A_i^n, and on superior level a structure St^{n+1}, characterized by the attributes A_i^{n+1}. In this case, the elements of the lower structure form the superior structure:

$$\bigcup_{j=1}^{p} St_j^n = St_k^{n+1} \quad (9)$$

but the attributes A_i^{n+1}, cannot be considered as the union of the attributes A_i^n , because the characteristics are related essentially to the positional relationships between elements, the mean values obtained by granular observation, and the structure's visible side projection. Thus, it can be concluded that, depending on the granularity of the observation, different structural level with corresponding attribute sets can be distinguished. These sets are not determined by the resolution of the obtained image, but are in dependence only with the level of the structure that is observed. For example, a man who is observed on a large distance, is characterized by his shape, but if he is observed on close distance, he can be characterized by the skin color of his face.

From this conclusion it can be derived that sometimes the same object which appears in imagines obtained from different video cameras at the same time, cannot be labeled according to the same patterns, because the granularity of the object is different. Thus, the process of transformation to the same granularity is not necessary. Instead, different attributes matching different granularities must be applied, or, if a high continence exists in the information provided by one video camera, only that image can be analyzed. For example, such a situation can occur in object tracing, when the distance between the object and the video cameras has an important variation. In these cases the labeling attributes must change.

If more that one attribute characterizes an object, and these attributes are related to the granularity of the observation, it results that for a set of granularities, a determined attribute can be used. The question is which of these granularities is best for features extraction. Obviously, those that creates a better "contract" should be used; this means that the granularity which has the most sharpest delimitation of the attributes clustering should be used. Several such fuzzy ways of clustering are presented in [8]. In this article a method based on a modified relationship of entropy will be used.

It must be remarked that, together with the monotonic changing of the granularity, the shape of the clustering borders is continually changing. But by having a digital image, a finite number of granularities can be computed and the result is not guarantied to be optimal. Thus, for every element in the range of the granularity corresponding to one attribute set, an objective function of uncertainty will be determined, using the relationship:

$$H(U) = -\sum_{i=1,N}(U_i \cdot \log U_i)\ (10)$$

where

N is the number of attributes and I is the degree of uncertainty obtained by subtracting the degree of dissimilarity D from the global similarity S: $U=S-D$. The normalized form can also be used:

$$U^* = \left|\frac{S-D}{S}\right| = \left|1-\frac{D}{S}\right|\ (11)$$

The best granularity is selected to be that for which the objective function has the lower point:

$$G_{opt} = \{G_j \mid H_j = \min_{j=1,N} H(U)\}\ (12)$$

It must be underlined as the main conclusion that for the same object observed on monotonic varying distances a variation of the objective function will result. As it passes through the domain of granularity, it will pass from one range to another, and from one sets of attributes to another. For every range, the best granularity that corresponds to the minimum odd uncertainty can be determined.

III. EXPERIMENTS

A set of 3x3x8 experiments with features extracted from images was performed, using a elongated, a round and a elliptic object, and for each creating three illumination condition. Two MDV213 type video cameras were used. For obtaining a 3D information, a triangulation process was performed based on the method presented in [7]. Two sets of attributes were used: one for long distance feature recognition based on human shape, and one for short distance feature recognition based on skin color and face shape. The shape extraction was performed by extracting the area and the second order moment from the images. The segmentation was made using the background extraction. The experiments are simple, but suggestive for the purpose of this paper. It was determined experimentally that the attributes sets were change, approximately at a range of 4 meter from the cameras. For long ranges, the prototypes were geometric shapes like elongated, round or elliptic forms. For short ranges, different colors like yellow, orange, red blue and green were used; the set of shapes used in long-range recognition was used here as well.

IV. CONCLUSIONS

Surveillance techniques are mostly based on information provided by video cameras. In this article, a granularity-based method is presented. The result is obtained by applying three procedures.

First a video recognition is used by establishing the best granularity for one of the attributes sets corresponding to the distance range, and then determining an uncertainty degree for these features. This method is based on two fuzzy relationships: the similarity and dissimilarity of the unknown feature, which is required to be labeled, and the two most nearest prototypes. It had been proved that the method is sound, and leads to good results. The method can be generalized by taking into consideration the k-nearest neighboring prototypes for determining the dissimilarity measure. Further investigation will be done in this direction.

In the second stage, a granularity-based localization and heating surface estimation is performed using the infrared detectors. The information provided by this type of sensors has a rough granularity, and the estimation is based on observing a sequence of simultaneously activated outputs. Previously, a fuzzy characteristic determination is necessary to be performed for the detectors.

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