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Change Detection in Video Surveillance Based on Fuzzy K means Clustering and Block Matching

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ABSTRACT : *The main objective of this paper is to detect changes in the optical images of the same area acquired over different times based on Block Matching and Fuzzy Clustering algorithm. The proposed Fuzzy k means clustering is combined with block matching, is less time consuming and do not need any priori knowledge of distribution of changed and unchanged pixel . Inorder to reduce the iteration steps and computation time fuzzy clustering is performed prior to Block Matching. Noises caused by imaging effects or camera jitter can be reduced, and change detection [1] based on Block Matching and Fuzzy k means clustering algorithm becomes feasible. The change detection results obtained by Block Matching and Fuzzy k means clustering algorithm exhibits enhanced tolerance to noises and illumination changes.*

Keywords - *Block matching ,Change detection ,Clustering ,Fuzzy k means clustering.*

1. Introduction

Image change detection is a process that analyzes images of the same scene taken at different times in order to identify changes that may have occurred between the considered acquisition dates [5]. In the last decades, it has attracted widespread interest due to a large number of applications such as remote sensing [6], medical diagnosis [7],[8], video surveillance [9], [10], useful to identify vegetation changes, monitoring shifting cultivations, studies on land-use/land-cover dynamics, burned area assessment, monitoring urban growth *etc*. With the development of remote sensing technology, change detection in optical images becomes more and more important. Among them, change detection in synthetic aperture radar (SAR) images suffers from the presence of the speckle noise [1] .However, SAR sensors are independent of atmospheric and sunlight conditions, optical images are affected by atmospheric conditions and illumination effects which make the change detection in SAR images still attractive. The whole performance of optical image change detection is mainly relied on the accuracy of the classification method .Block matching and fuzzy k means clustering are used to identify the change areas in the difference image, without any distribution assumption.

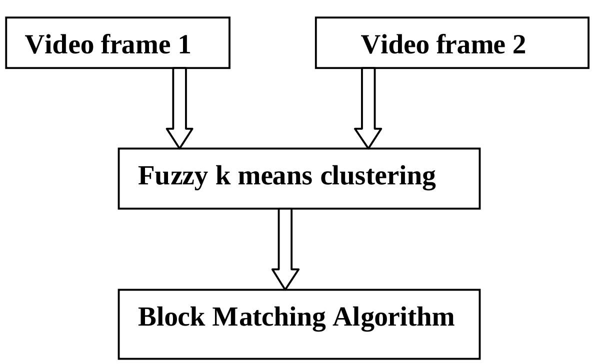

Fig 1: flow chart of proposed change detection approach

The optical images are analyzed using Block Matching and Fuzzy K means Clustering algorithm (FKC). The purpose to analyze the optical images is to discriminate changed regions from unchanged regions which is shown in fig 1. A fuzzy k-means clustering algorithm and block matching that is insensitive to the probability statistics model of histogram is proposed to analyze the difference image.

This paper is organized as follows: First, in section, we briefly explain block matching II and its techniques. We then outline the Flow chart of Block matching. In section III a brief description about clustering is given. The proposed algorithms are discussed in section IV and V. Experimental results are shown in Section VI. Finally, the paper is concluded in Section VII.

2. Block Matching

Detection of objects is difficult due to camera noise, lighting conditions, object orientation and size. Detection is primarily done by preprocessing the frame to reduce noise and the effect of different lighting conditions, followed by Block Matching [2]. In block matching, blocks in the current frame are matched to blocks in a reference frame (an earlier frame). For each block in the current frame, the reference frame is searched for the best matching block. A matching criteria determines the best match from candidate blocks in the reference frame. If the matched block is not in the same location in the reference frame as in the current frame, the block has moved. A foreground mask of the moving blocks is generated. Blocks with the same motion can be combined to form moving objects. Block matching adds the additional information of block motion, making block matching attractive for tracking applications. Block matching is extensively used in compression to detect objects.

2.1 Block Matching Techniques

Block matching techniques match blocks from the current frame with blocks from a reference frame. The displacement in block location from the current frame to the location in the reference frame is the motion vector. Block matching techniques can be divided into three main components as shown in Fig 2: block determination, search method, and matching criteria.

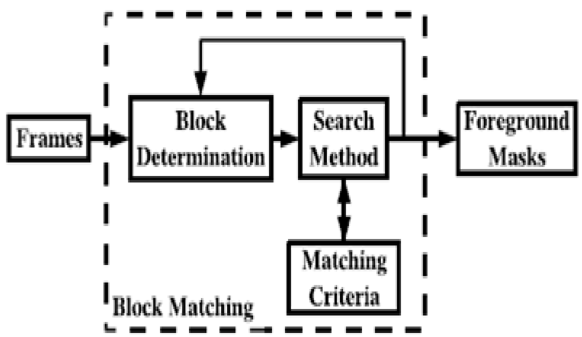

Fig 2.block matching flowchart

The first component, block determination, specifies the position and size of blocks in the current frame, the start location of the search in the reference frame, and the scale of the blocks. We focus on fixed size, disjoint blocks spanning the frame, with initial start location at the corresponding location of the block in the reference frame. In tracking, a predictive method may be used to improve the start location of the search.

The search method is the second component, specifying where to look for candidate blocks in the reference frame. A fully exhaustive search consists of searching every possible candidate block in the reference frame. This search is computationally expensive and other search methods have been proposed to reduce the number of candidate blocks and/or reduce the processing for all candidate blocks.

The third component is the matching criteria. The matching criteria is a similarity metric to determine the best match among the candidate blocks. In faster search methods, the best match so far will also determine the direction of the search (choice of next candidate blocks). The motion vectors are fed to the block determination to implement multi resolution blocks. A coarse to fine resolution of the blocks is generated. The start location of the search at each resolution is the location of the best match (motion vector).

3. Clustering

Clustering techniques [3] are mostly used to organize data into groups based on similarities among the individual data items. Clustering algorithms can be exploited in a wide variety of applications, including classification, image processing, pattern recognition, modeling and identification .A cluster is a group of objects that are more similar to one another than to members of other clusters. The performance of most clustering algorithms is influenced not only by the geometrical shapes and densities of the individual clusters, but also by the spatial relations and distances among the clusters. Clusters can be well-separated, continuously connected to each other, or overlapping each other. The data are typically observations of some physical process. Since clusters can formally be seen as subsets of the data set, one possible classification of clustering methods can be according to whether the subsets are fuzzy or crisp (hard).

Hard clustering methods are based on theory that an object either does or does not belong to a cluster .Hard clustering means partitioning the data into a specified number of mutually exclusive subsets.

Fuzzy clustering methods allow the objects to belong to several clusters simultaneously, with different degrees of membership. Objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership.

4. Block matching algorithm

Exhaustive Search (ES) algorithm [2],also known as Full Search, is the most computationally expensive block matching algorithm of all. This algorithm calculates the cost function at each possible location in the search window. As a result of which it finds the best possible match and gives the highest PSNR amongst any block matching algorithm. Fast block matching algorithms try to achieve the same PSNR doing as little computation as possible. The obvious disadvantage to ES is that the larger the search window gets the more computations it requires. So in priori, clustering is performed using fuzzy k means clustering algorithm.

5. Fuzzy k means clustering algorithm

The fuzzy *k*-means clustering algorithm [4] partitions data points into k clusters S_l (l = 1, 2,…, k) and clusters S_l are associated with representatives (cluster center) $\mathbf{C}_l$. The relationship between a data point and cluster representative is fuzzy. That is, a membership $u_{i,j}$ Є [0, 1] is used to represent the degree of belongingness of data point $\mathbf{X}_i$ and cluster center $\mathbf{C}_j$. Denote the set of data points as $S = \{\mathbf{X}_i\}$. The FKM algorithm is based on minimizing the following distortion:

$$J_m = \sum_{j=1}^{K} \sum_{i=1}^{N} u_{i,j}{}^{m}\, d_{ij} \quad \text{……………………………………... (1)}$$

with respect to the cluster representatives C_j and memberships $u_{i,j}$, where N is the number of data points; m is the fuzzifier parameter; k is the number of clusters; and d_{ij} is the squared Euclidean distance between data point X_i and cluster representative C_j. It is noted that $u_{i,j}$ should satisfy the following constraint:

$$\sum_{j=1}^{K} u_{i,j} = 1, \text{for } i = 1 \text{ to } N \quad \text{……………………………… (2)}$$

The major process of FKM is mapping a given set of representative vectors into an improved one through partitioning data points. It begins with a set of initial cluster centers and repeats this mapping process until a stopping criterion is satisfied. It is supposed that no two clusters have the same cluster representative. In the case that two cluster centers coincide, a cluster center should be perturbed to avoid coincidence in the iterative process. If $d_{ij} < \eta$, then $u_{i,j} = 1$ and $u_{i,l} = 0$ for $l \neq j$, where η is a very small positive number.

6. Experimental result

Experiments are conducted on different frames of a video and detect changes based on Block Matching and Fuzzy k means Clustering algorithm.A traffic video (120 frames) with various illumination conditions were taken. The moving object was identified by program and manualy. Then measure the PSNR value based on the moving object identified. The change detection results exhibits enhanced tolerance to noises and illumination changes. Out of the 120 frames with various illumination conditions 4 frames are taken which is shown in fig (4).

fig 4: experimental results of traffic video

30 frames of the result after eliminating the illumination condition are taken and the PSNR value is calculated and the graph is drawn as shown in fig (5).

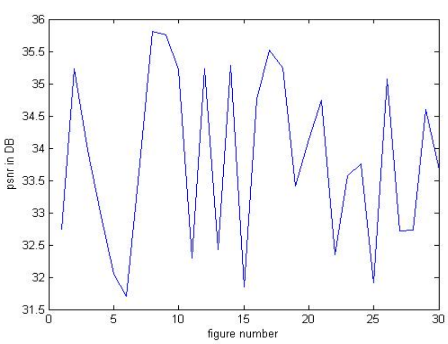

fig 5: number of frames vs PSNR in db

Mean PSNR value obtained is 34.1514

Minimum PSNR value obtained is 31.7013

Maximum PSNR value obtained is 36.3408

7. Conclusion

In this paper, we have presented a change detection approach on video surveillance based on Block Matching and fuzzy k means clustering algorithm. The whole performance of change detection is mainly relied on the accuracy of the classification method. Block matching and fuzzy k means clustering are used to identify the change areas in the difference image, without any distribution assumption. The obvious disadvantage to ES is that the larger the search window gets the more computations it requires. So in prior to Block Matching, clustering is performed using fuzzy k means clustering algorithm to reduce the iteration steps. Enhanced tolerance to noises and illumination changes is proposed by Block matching and FKM algorithm.

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