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An Effective Image Differencethreshold Strategies and Shadow Detection

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Abstract: The paper considers two problems associated with the detection andclassification of motion in image sequences obtained from a static camera.Motion is detected by differencing a reference and the "current" image frame and therefore requires a suitable reference image and theselection of an appropriate detection threshold. Several threshold selectionmethods are investigated and an algorithm based on hysteresisthresholding is shown to give acceptably good results over a numberof test image sets. The second part of the paper examines the problemof detecting shadow regions within the image which are associated with the object motion. This is based on the notion of a shadow asa semi-transparent region in the image which retains a (reduced contrast)representation of the underlying surface pattern, texture or greyvalue. The method uses a region growing algorithm which uses a growingcriterion based on a fixed attenuation of the photometric gain overthe shadow region, in comparison to the reference image.

Key words: Motion · Acceptably good · Problemof detecting · Ssociatedwith

INTRODUCTION

Frame differencing is a particularly efficient and sensitive method for detectinggrey level changes between images which are co-registered. It is widely used inmotion detection, where a fixed camera is used to observe dynamic events in ascene.

The frame differencing algorithm may be sub-divided into three parts: firstly,the generation of a suitable reference or background; secondly, the arithmeticsubtraction operation; and thirdly, the selection (and application) of a suitablethreshold. Reference images can be generated by a variety of methods, e.g. on abackground image acquired during a period of relative inactivity within the sceneor from a temporally adjacent image from a dynamic sequence. In order to adaptto both global and local illumination changes (e.g. clouds, shadows), updatingstrategies can be applied to the reference image in order to keep it up-to-date. Another problem in motion estimation occurs because of the detection of shadows,generated as the result of bright point-like illumination sources. These shadowsmay either be in contact with the detected object, or disconnected from it.

In the first case, the shadow distorts the object shape, making the use of subsequentshape recognition methods less reliable. In the second case, the shadow may be classified as a totally erroneous object in the scene. For analysing manynatural world scenes (e.g. [1]) the disambiguation of these shadow regions wouldsubstantially benefit the object classification.

Change Detection: We assume a stationary camera; any movement (e.g. caused by wind shaking thecamera) is corrected by first translating the images in the sequence (generally bya small amount) with respect to any image in the sequence or to some referenceimage such that their cross-correlation is minimised. Change detection can then beperformed by simply taking image differences [2]. The differencing can be performedbetween subsequent frames in the image sequence (e.g. [9]). This has the advantagethat little spurious change should occur in the small time gap between frames.

But the disadvantages are: 1/ that only the motion "wavefront" will produce anychange, so that only part of the moving object is highlighted and 2/ objects thatbecome stationary for short periods of time will "disappear". The alternative isto difference the image

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sequence against some reference image representing thebackground. If the background image is acquired some time previously (whenit is known that no unwanted foreground objects were present) then there is adanger that changes in the ambient conditions (e.g. position of light source, light intensity), will cause the background image to become outdated. Therefore apotentially more robust approach is to dynamically generate the background imagefrom some portion of the image sequence.

Background Generation: The task is as follows: the background image *Bx,y*is to be generated from asequence of images *Itx,y*which may contain moving objects. One approach takes an estimate of the background generated from the previousframes and updates it using the current frame, which can be formulatedas a Kalman filter [3]. However, various parameters are required which specifythe degree of smoothing the previous estimates have on the current backgroundprediction and the model for background change (e.g. constant rate of change).Alternatively, Long and Yang [4] analyse the temporal signature at each pixelfor a stable section, i.e. a sequence of values which only changes by small amountsover time. The disadvantages are again the need for various parameters as well asthe requirement of a continuously unoccluded view of the background.Our approach is to perform background detection using L-filters, i.e. a linearcombination of the ordered samples of the image sequence [5]. This has several advantages:since the data sequence is (re)ordered it is not dependent on the backgroundappearing unoccluded over a continuous sequence; L-filters are a class of robuststatistics and can tolerate large amounts of (e.g. non-Gaussian) noise and; itdoes not require parameters.

Previously we have generated the background using a median filter at eachpixel [6]: *Bx,y*= med*t Itx,y*. Alternatively, Yang and Levine [7] have suggested the least median of squares (LMedS) estimate: *Bx,y*=min*b*med*t_Itx,y*.

Automatic Thresholding of Difference Images: A popular approach to performing the automatic thresholding of difference imagesis to assume particular distribution models for the difference of image samples andthe noise [8-10]. Instead our first method uses simple methods from robust statistics and doesnot require any distribution assumptions. We analyse the difference image *Dx,y*= |*Ix,y* - *Bx,y*| to determine the median MED = med*x,y?IDx,y*and the medianabsolute deviation MAD = med*x,y?I* |*Dx,y* - MED|. Assuming less than half theimage is in motion the median should correspond to typical noise values and a suitable threshold is at *T* = MED+3 × 1.4826 × MAD*,* where 1.4826 is anormalisation factor wrt. a Gaussian distribution.

Connectivity Preserving Thresholding: In the context of document analysis O'Gorman [11] proposed a technique for imagethresholding based on image connectivity. The image was thresholded at multipleintensities and the connectivity value of each calculated. The threshold wasselected from an intensity range that produced a stable set of connectivity values.Rather than measuring connectivity, the number of regions may be more appropriate.

However, the advantage of calculating connectivity over region countingis that the Euler number is locally countable [12] and can therefore be determinedefficiently in a single raster scan of the image. We have experimented with calculatingboth the number of regions and the Euler number at all possible thresholds.The mode of the measures is calculated and the threshold is selected as the lowest difference intensity that produces the mode value. We have found both thetopology and connectivity methods give very similar results.

Thresholding with Hysteresis: In his influential paper on edge detection Canny [13] popularised the application ofconnectivity-based hysteresis to thresholding. A bilevel edge magnitude thresholdis applied, producing three classes of edges. All edges above the high threshold areretained (class *H*) and all edges below the low threshold are rejected (class *L*) [14]. The remaining edges (class *M*) are retained only if they are adjacent to class *H*edges or are connected to class *H* edges via other class *M* edges. The advantageof applying hysteresis is that it incorporates spatial context into the thresholdingdecision and effectively enables isolated (noisy) medium strength edges to beeliminated without fragmenting long curves containing low strength sections.

We can apply the same technique of incorporating context to region thresholdingas a method for eliminating small noisy regions without fragmenting largerregions. The difference image is thresholded at two levels and regions in the intermediaterange of intensities are rejected unless they are connected to regionsgenerated by the lower threshold. Determining the connectivity is implemented byiteratively dilating the high threshold image and performing a logical and withthe low threshold image. This has the advantage that it can be done relativelyefficiently. Also, if desired, the amount of expansion of the high threshold imagecan be controlled by limiting the number of dilation iterations.

Canny experimentally determined that a ratio of 2:1 between upper and lowerthreshold values produced good results. In [15] this was formulated as

R =ln 2ln 1+2P1+P

where P is the probability of an edge (and 1-P is the probability of a non-edge).In this context Canny's ratio is obtained when P = 0.23 which may be a reasonableassumption for typical edge maps.We can apply the same reasoning to determining the threshold ratio for applyinghysteresis to the difference images. Our sequences tend to only have small areasof motion, normally in the range P = [0.01, 0.05], which gives R = [8.39, 3.86].

An alternative approach is to use a hybrid threshold selection scheme, wherethe upper and lower hysteresis thresholds are selected by different methods.

Local and Global Information: It should be noted that the hysteresis methodology attempts to combine local andglobal information: the two thresholds are calculated globally while the thresholdingin the intermediate range uses local information. Local and global information have also been combined in different ways by other thresholding methods. Song *et al*. [16] use a single high threshold on the difference image and then grew thethresholded regions. This, however, assumes that both the moving objects andthe background are homogeneous. Yang and Levine [7] determine individual pixel thresholds by the following:

- The background image *Bx,y*is generated using the LMedS criterion as describedin section 2.1.
- A threshold image *Tx, y*is generated from the median absolute deviation (MAD) at each pixel *Tx, y*= *Bx,y* + 2.5 × 1.4826 × MAD*x, y*, where MAD*x,y*=med*t*
- For the set of values in the difference image above their local thresholdthe global statistics (LmedS *g* and MAD*g*) are calculated. An additionalthreshold is applied to those previously retained pixels: pixels with differencev alues less than or equal to LMedS*g*+ 2.5 × 1.4826 × MADgare removed.In addition, local outliers are removed by non-maximal suppression and erosionand dilation is performed. In our experiments these additional stages were notincluded – they were used by Yang and Levine [7] since they differenced edgemaps and wanted connected contours. The calculation of the MAD was modifiedaccording to Rousseeuw and Leroy [17] to take into account a finite samplecorrection factor which they determined as 1 + 5*n*-*p*, where *n* is the number ofdata samples and *p* is the data dimensionality. For our examples containing shortimage sequences, this factor is substantial (e.g. 1.7 for n = 8 and p = 1).

Computational Efficiency: Both the median and LMedS methods for background generation can be simplyimplemented based on sorting the F frames (each containing P pixels) in the sequence and so their computational complexity is $O(PF \log F)$.

For determining the thresholds the three methods are:

- Calculating the global MED and MAD of the difference image can be calculatedin $O(P)$ time using the histogram method [7].
- The Euler number only requires a single raster scan and is applied at all *G*grey levels and is therefore $O(GP)$.
- The per pixel MAD method suggested by Yang and Levine [7] requires$O(PF \log F)$ to generate the threshold image. Using the histogram methodLMedSgand MADgare calculated in $O(P)$ time [18].

We use a simple iterative raster-scanning method for performing the hysteresis.If I iterations are required then the complexity is $O(PI)$. However, if propagationis restricted to the blob boundaries then more efficient methods could be designed.

Examples of Thresholding: The alternative methods for the individual stages of processingproduces a large number of possible combinations. Due to limitations of space wewill describe results for only some of these combinations.

Figure 1a shows the first of eight frames from sequence srdb018 in which amoving bird is located in the centre of the image. Note the low dynamic range,poor contrast between the bird and background and the small size of the target. The following examples of thresholding

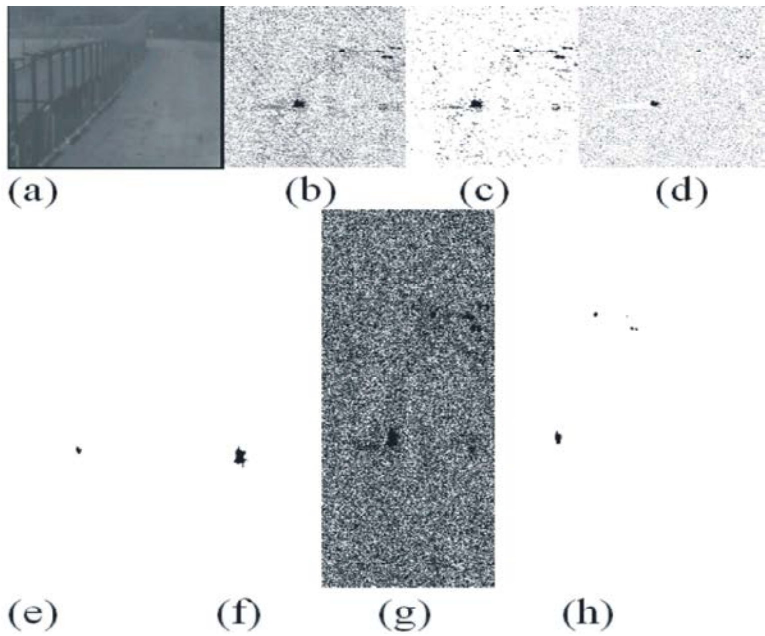

Fig. 1: Srdb018 (a) Frame 1, (b) median, (c) median(difference) + median,(d) LMedS background + local thresholds, (e) median(difference) + Euler, (f) median(difference) + Euler + hysteresis, (g) Otsu, (h) median(difference) + Otsu

show only the right half of the image. Detectingthe background using the median method and then thresholding based onthe median and MAD (section 2.2) of the difference image gave very noisy results (Fig. 1c). Median filtering the difference image first improved the results, but thereare still many noisy blobs (Fig. 1c). Using the LMedS method for backgrounddetection gave similar results as above. The local threshold approach of Yang and Levine [7] (without the non-maximal suppression and erosion/dilation stages) also gave noisy results (Fig. 1d). The connectivity method applied directly to thedifference image failed to detect the moving object. Instead four tiny bright noisepoints were retained instead since they persisted over a large range of thresholds.

However, when the difference image was median filtered, removing these points, asingle blob was retained, corresponding to the bird (Fig. 1e). It can be seen thata high threshold was necessary to eliminate all other blobs, resulting in the targetblob being shrunk since its boundaries are blurred. Applying hysteresis thresholding(R = 8) produces a good result (Fig. 1f). The bird is well thresholded whilstalso avoiding spurious blobs. For comparison, some standard image thresholdingtechniques were also applied [19-21]. Without median filtering the differenceimage Otsu's method performed very poorly (Fig. 1g), but with the addition offiltering it gave the best result of the three techniques (Fig. 1h).

A second example is given in fig. 2a of the first of eight frames from sequencesrdb044 showing a man walking in the shadow at the rear of the scene. Again,the connectivity method with prior median filtering of the difference image and hysteresis performs well (fig. 2b) - a single blob is extracted corresponding to theman. The other methods give poor results (eg. the median method applied aftermedian filtering of the difference image, fig. 2c). Otsu's method underthresholds,and the man is fragmented into four blobs (Fig. 2d).

Shadow Detection: Previous research on the detection of shadows [22-24] has focused on two mainuses: disambiguation for object recognition and recovery of the underlying surfacedetail. Here we consider only the former problem.We can interpret shadows in the image and the effect they have on the pixels inthe scene, as a semi-transparent region in which the scene reflectance undergoes alocal attenuation. Under the constraint that the imaging sensor is not undergoingmotion, it is feasible to identify those regions within shadow by analysis of theirphotometric properties: firstly, they will have a photometric gain with respect to the background image, which is less than unity; secondly, this gain will bereasonably constant over the shadow region, except at the edges, where the effectsof a finite size illumination source will tend to reduce the attenuation (i.e. thepenumbra). Although similar photometric

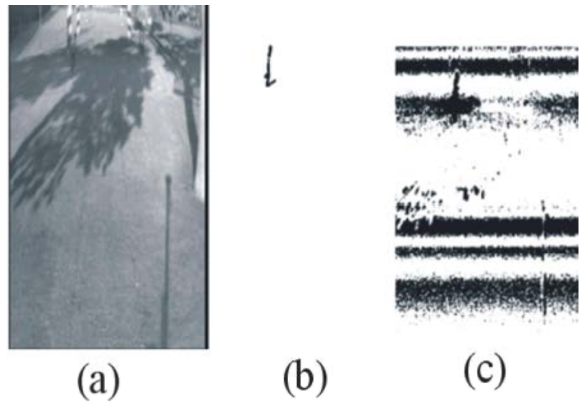

Fig. 2: Srdb044 (a) Frame 1, (b) median(difference) + Euler + hysteresis, (c)median(difference) + median

characteristics may also be exhibitedby actual objects in the scene (i.e. those that are darker than the background andhave a uniform gain with respect to the surface they occlude), there occurrence isexpected to be less likely and hence they may be interpreted as rare “accidents”.The shadows are modelled as a constant contrast chage between the referenceor background image and the current image and are detected by performing region growing to locate areas of constant photometric gain in the difference image Heuristic rules are then used to cue possible shadow regions.

Region Growing: The algorithm starts with a thresholded image resulting from a frame differencingoperation, generated using one of the methods described earlier in the paper. Thealgorithm calculates for each pixel within the binary detected blobs the intensityratio between the current and background image. A single pass neighbourhoodconnectivity algorithm [8] is used for region growing, which performs a rasterscan through the image, propagating region labels based on local eight-neighbourconnectivity using constant values of the intensity ratio (i.e. the gain). The gainis simply defined as the ratio of the reference pixel intensity to the image intensity,*gainx,y*= *Rx,yIx,y*, resulting in ratios of less than unity in regions where the image isbrighter than the reference and greater than unity where it is darker.

For each of the four previously examined neighbours in the raster scan (whichwill already have been assigned a region label), the minimum difference betweenthe pixel gain and the mean gain of each of the regions is used to identify intowhich region the pixel might be merged. If the gain is less than some prescribedthreshold, then the pixel is labelled as belonging to that region and its gain is usedto update the region mean and variance; otherwise, a new region is initiated.A second stage of the algorithm merges similar neighbouring regions by usinga t-test to compare the mean and variance of each pair of neighbouring regions.A significance level of 0.05 was used.

Shadow Identification: Following region growing, several rules are applied to the analysis of local regions todiscriminate the shadow regions from the object. In the first instance, the variationof region statistics within the shadow region should vary smoothly and the shadowregion should contain relatively homogeneous intensity ratio regions. Secondly, thegain values within the shadow region should always be less than unity (i.e. thepixels in the shadow region will be darker than those in the reference image). The homogeneity of the region is estimated by considering it’sneighbours. The proportion of a regions’ boundary which is shared with other regions is computed,and the ratio of the boundary shared with the background, against thetotal boundary length is determined. Secondly, the area of all directly borderingregions is calculated and expressed as a proportion of the regions own area. Thesetwo values are thresholded to select homogeneous regions that have no substantialborder with other regions which have no significant similarity in the gain ratio.

RESULTS

Fig. 3a shows a composite image of a person walking through a car park. A referenceimage frame of the background is from the first frame in the sequence,acquired several seconds before the person enters the field of view. The shadowsobtained are fairly strong, though they contain some significant brightness variationswithin the shadow region (i.e. the white lines). Fig. 3b shows the result ofbinary thresholding the

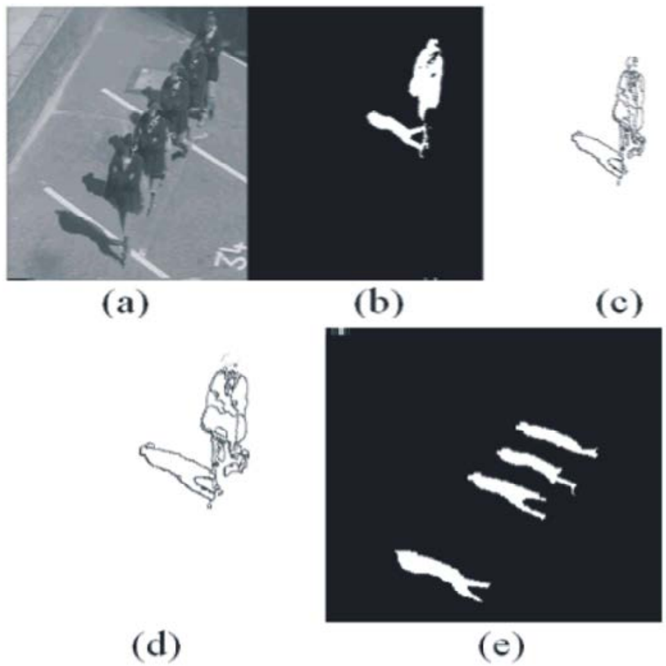

Fig. 3: Shadow (a) Grey-level composite (5 frames), (b) frame differenced andthresholded, (c) first region boundaries, (d) second stage regions, after merging,(e) composite of shadow classified regions

difference image. The results of the first stage of regiongrowingare shown in Fig. 3c, where it can be seen that both shadow and object aredivided into a number of regions. The regions resulting from the merging operationare shown in fig. 3d. The shadow has been detected as mainly a single region,whilst the person (which is composed of a number of regions of significantly differentgrey levels), remains fragmented. The final classification of the shadow regionsis shown in Fig. 4e. In this composite taken over all 5 images in the sequence, theshadow detection fails to find the shadow for the 4th frame, which violates oneof the identification rules used above and is found to contain an internal regionwhich is classified as background, resulting from light passing between the legs [25].

DISCUSSION

Our initial results show that the most reliable method for thresholding a differenceimage to obtain the target blobs without spurious clutter is to first median filter the difference image and then use the connectivity thresholding methodfollowed by hysteresis. Comparisons were made with several other thresholdingapproaches, including those designed specifically for difference images as well as some more general standard image thresholding methods. More substantial verificationis under progress using a larger test set. While it would be desirable touse performance measures to objectively rate the various appoaches, our initialexperience with several such measures has found little correlation between theirratings and subjective assessment.The shadow detection algorithm seems to perform well on the image sequencesthat we have applied it to. However, several observations may be made on theexperiments thus far. The shadow regions will be easier to find in images containingmany (moving) objects that create shadows, since the photometric gaincan be expected to be fairly constant over the image and to exhibit a reasonable temporal constancy. The region growing algorithm can be affected by the shadowpenumbra, though the application of a binary erosion operator, applied to theoriginal differenced image can significantly minimise any deleterious effects. Someof the initial observations on the characteristics of the shadows (especially associatedwith enclosed regions of significantly differing gain values) do not hold upwell in practice. In particular, objects in the scene which are transparent (or semitransparent) will contradict the assertion that the shadow should be homogenous.Further work is also in progress to investigate the potential for discriminating shadows from colour sequences and at methods of identifying the shadows in datawhere the camera is not stationary [26-28].

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