The Effects of Motion and Spatio-temporal Non-uniform Illumination on Image-pair Joint Scattergrams

Michael E. Farmer[§] and Sushma Kittali*
Department of Computer Science, Engineering Science and Physics,
University of Michigan-Flint
*Email: [§]farmerme@umflint.edu, *kittali@umflint.edu*

Abstract

Accurate and robust image change detection and motion segmentation has been of substantial interest in the image processing and computer vision communities. Spatio-temporal illumination effects such as complex lighting effects involving moving light bands or moving shadow bands can confuse existing motion segmentation algorithms, which are based on analysing the greyscale image directly. While efforts have been made to improve the robustness of motion segmentation algorithms under varying illumination, the results to date are still not completely satisfactory. We propose using the joint scattergram between two images as the representational space for analyzing motion. These scattergrams have properties which can distinguish motion from complex illumination changes. We verify these properties of the scattergram on image datasets captured in the laboratory as well as outdoors and show its utility as a robust representational domain.

1. INTRODUCTION

Object motion in a sequence of images is a very powerful cue for performing segmentation of objects of interest from the background. Detection and segmentation of objects based on the motion in images can be performed in a number of ways [1][2][3]. None of these methods have been shown to be generally superior.

It is important to note that all of these methods operate on the grayscale imagery. The grayscale image space, however, is the result of a complex interaction of: (i) the motion of object of interest, (ii) its surface characteristics, and (iii) the external illumination pattern [2][3]. We propose viewing image sequences in an alternative representational domain where the effects of illumination are distinct from the effects of motion.

The use of information theoretic measures such as entropy and mutual information have been gaining popularity in a variety of applications, including: image registration, image similarity testing, and image subtraction [9][10][11]. Most of these methods begin with the generation of the joint scattergram between the two images as a means of estimating the joint probability density function.

In this paper we demonstrate that the joint scattergram can be used to robustly distinguish illumination changes from the changes due to the motion of the object.

2. BACKGROUND OF ILLUMINATION MODELING

There are two elements to the motion segmentation problems that a successful algorithm must provide: (i) sensitivity to motion of the objects in the image, and (ii) insensitivity to the effects of spatio-temporal illumination changes. Negahdaripour has hypothesized that the illumination effects in imagery are either additive or a multiplicative behavior, where [2]:

- the multiplicative factor is due to changes in object surface orientation
- the additive factor corresponds to the variations in diffuse illumination.

Other researchers have also modeled illumination effects using either additive or multiplicative linear models [4][5][6][8]. These effects can be seen mathematically by recalling the equation for scene radiance, L, under the assumption of Lambertian reflectance [4][12]:

$$L = \rho \vec{N} \cdot \vec{I}, \qquad (1)$$

where ρ is the albedo of the surface, $\vec{N}$ is the normal to the surface of the object, and $\vec{I}$ is the directional illumination. If the changes in external illumination are multiplicative, then they would enter Equation (2) as a scale to the illumination $\vec{I} \cdot \lambda$, and the change in reflectance seen by the camera would be L_m [7]:

$$L_m = \rho \vec{N} \cdot \vec{I} \cdot \lambda \qquad (2)$$

We will show in Section 4.1 that the effects of illumination change are indeed multiplicative.

Note more complex reflectance models such as the Torrance-Sparrow model which combines specular and diffuse components of scene radiance, maintain this basic form of the illumination multiplied by a surface descriptor, which implies illumination changes can be modeled either multiplicative or additive contributions [5]:

$$L = \left(K_d + K_s\right) \cdot \vec{I}\ , \tag{3}$$

where K_d is the diffuse component, and K_s is the speculative component of the surface.

3. PHENOMENOLOGY OF IMAGE SCATTERGRAM

Mutual information, $I(A;B)$, between two images A and B can be defined as [9]:

$$I(A;B) = \sum_{a,b} p(a,b) \cdot \log\left(\frac{p(a,b)}{p(a)p(b)}\right), \tag{4}$$

where $p(a)$ and $p(b)$ are the individual distributions of images *A* and *B,* and $p(a,b)$ is the joint distribution of images *A* and *B,* and *a* is a value in image *A* and *b* is a value in image *B.* The joint distribution of two images can be approximated using the joint scattergram *S(a, b)*, where *a* and *b* are the grey levels in each respective image and the pair *(a, b)* provides the coordinate for the entry in the scattergram.

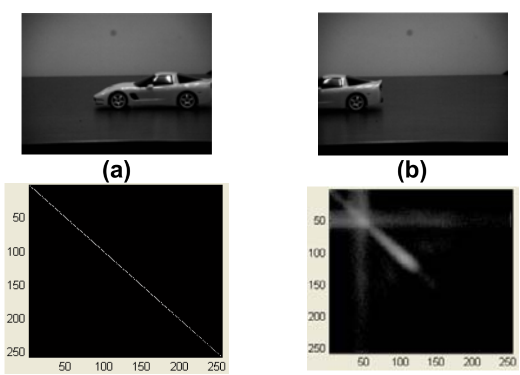


Figure 1: Scattergram behavior, (a) Original image, (b) second image in a sequence, (c) self-joint scattergram of first image with itself, and (d) joint scattergram between the two images.

When a scattergram is generated from an image with itself, the result is a well defined ridge (See Figure 1 (c)) corresponding to the straight line *a* = *b*, where *a* and *b* are the grey levels in each respective image. Likewise, Figure 1 (d) shows the scattergram of between the two images in the sequence, and we can see the dramatic effect motion has on the joint scattergram.

3.1. Scattergram Under Global Illumination Changes

In Figure 2 we artificially inject additive and multiplicative illumination changes into an image pair to understand the effects on the joint scattergram *S(a, b)*. Notice that the illumination change results in linear transformations in the scattergram, with multiplicative illumination resulting in a change in the slope of the ridge in the scattergram. Note also that the scattergram ridges are all well structured with no dispersion.

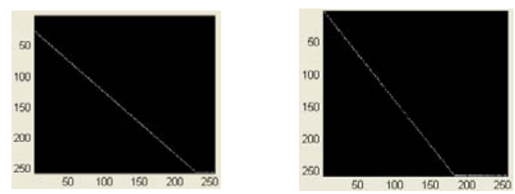


Figure 2: Joint scattergrams for image in Figure 1a) with a copy of itself with: (a) global additive illumination change of $\Delta\vec{I} = 25$, and (b) global multiplicative illumination change of $\lambda = 1.2$.

3.2. Scattergram Under Spatially Varying Illumination Changes

We analyze the effects of a realistic model for spatially varying illumination. We model partial illumination as a pattern with a Gaussian roll-off in amplitude along the boundaries. Figure 3 shows the images and their resultant joint scattergrams for an artificially injected additive and multiplicative illumination band with Gaussian-shaped roll-off. Note the general envelope of the scattergram matches that of the uniformly distributed illumination, with the internal structure of the envelope being generated by the Gaussian amplitude variations along the edges of the illumination pattern.

4. VERIFICATION OF SCATTERGRAM PHENOMENOLOGY

We have demonstrated the expected effects on the joint scattergram of the variations caused in an image sequence by global and spatially varying illumination. We will now verify these effects on image sequences collected in the laboratory and images from the well-known taxi cab sequence [13].

Since the scattergram of the entire image is the result of multiple motions, lighting effects, and noise, extracting multiple motions from this representation is difficult. Consequently, we propose dividing the image into regions, which we term mosaics, and then work with the scattergrams of these smaller mosaics. Russakoff, et al. has also proposed dividing the image into regions for using mutual information for image similarity analysis [11].

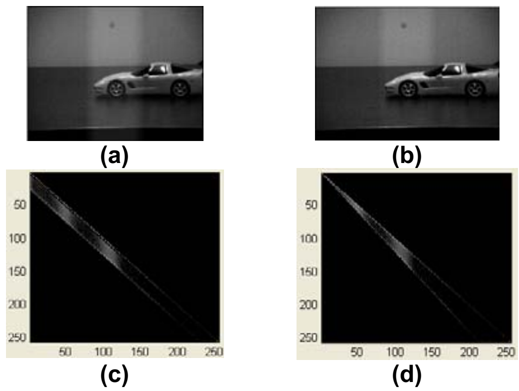


Figure 3: Artificially induced illumination effects on image in Figure 1 for illumination band with Gaussian-shaped roll-off, (a) image with partial additive illumination, (b) image with partial multiplicative illumination, (c) joint scattergram for (a), and (d) joint scattergram for (b).

4.1. Verification of Illumination Effects

Figure 4 demonstrates the effects of turning an overhead fluorescent light on while a toy car was moving. Note in the quadrants where there is no motion the clear change in slope of the diagonal in the image. Thus the illumination change is a *multiplicative* effect on the image, rather than additive. Note also the distinct linear characteristic

Figure 5 demonstrates the effects of temporally and spatially varying illumination in the form of a moving light band while a toy car was stationary. The illumination band was created by directing an incandescent light source through a rotating door-sized mirror so the light source moved smoothly across the scene. Figure 5 (c) and (d) clearly exhibit the distinctive triangular envelope of spatially varying multiplicative illumination in this joint scattergram space.

4.2. Demonstration of Motion Effects

Figures 6 and 7 demonstrate the effects of motion on the joint scattergram for two very different image sets: (i) the toy car laboratory images, (ii) the outdoor taxi cab images [13]. In the regions of the image where motion in present, the scattergram exhibits a strong non-linear behavior compared to the behavior seen for illumination effects.

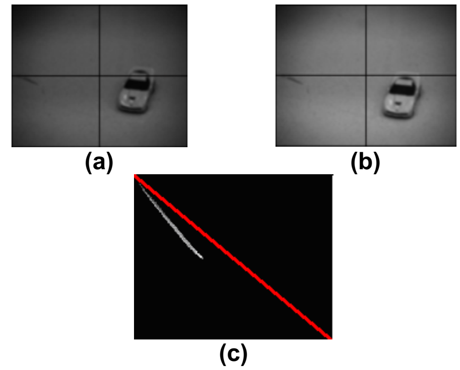


Figure 4: Scattergram under global illumination change, (a) Filtered first image, (b) filtered second image with added overhead lighting (c) joint scattergram between the two images for mosaic (row 1, col 1), annotated with unit diagonal (in red).

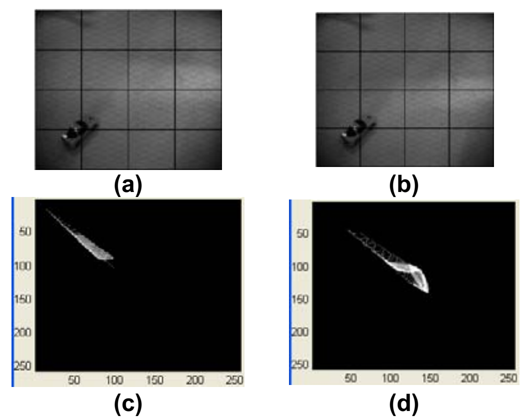
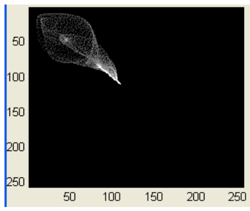


Figure 5: Scattergram for mosaics under moving spatially variable illumination, (a) toy car image at time 1, (b) toy car image at time 2, (c) scattergram of mosaic (row 3, col 1), (d) scattergram of mosaic (row 2, col 4).

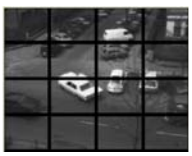
Note also the radical differences in the shapes of the scattergrams of each image set. These strongly non-linear effects are in stark contrast to the highly linear behaviors of the scattergrams under illumination change shown in Section 4.1. We processed hundreds of images from subsequences of both the toy car and the taxi cab sequence and found consistent phenomena. These similar patterns have been consistently present in hundreds of images from sequences of both laboratory and field collected datasets.

(a) (b)

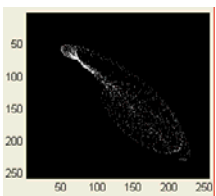


(c)

Figure 6: Scattergram behavior for toy car mosaics under object motion, (a) image at time 1, (b) image at time 2, (c) scattergram of mosaic (row 3, col 2) where car is moving.



(a) (b)



(c)

Figure 7: Scattergram behavior for taxi sequence (a) mosaic of first image, (b) mosaic of second image, (c), scattergram for mosaic region (row 3, col 2) where taxi is moving.

5. CONCLUSIONS & FUTURE WORK

We proposed using the joint scattergram domain, rather than the grayscale image domain for understanding change detection and object motion. We have demonstrated that the effects due to variations in illumination, which can be problematic for optical flow algorithms, can be modeled by linear processes while object motion clearly exhibits significant non-linearities in the joint scattergram.

Our future work will be directed at developing an algorithm to detect these differences in behavior to allow us to ignore image effects due to spatio-temporally varying illumination, while robustly detecting motion and other meaningful changes in image sequences.

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