Aryam Jain — Assignment-2 — 2019101056

section 1.1

1.) Slow motion videos can be created by resampling the original video or duplicating the frames. Optical Flow uses the relative motion of objects and surfaces to generate new intermediate frames results in smooth slow motion videos

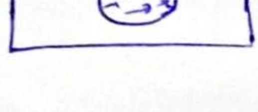
2.) In this scene, the fast moving bullet is being shown in slow motion along with the protagonist. The protagonist's evasive sequence is shot on a green screen and slowed down using informa^n generated using optical flow. The bullet & background is added using VFX / CG.

3.) In WDMC, the scenary is shot with a normal camera, Later, each pixel is assigned a paint stroke. Using optical flow, the movements of the various objects are used to pointer over the original scene. The characters are later added. This gives the "painterly effect".

4.) a) Under constant illumination (stationary light source), the rotating lambertian ball's 2D motion field will be on empty / static images.

b) In case of a stationary ball with a moving light source, the 2D motion will have points moving in ~~tn~~ to 1 diagonal.

Eg.



Section 1.2

1.) The following assumptions are made in optical flow estimation:

a.) Brightness Constantcy:- The object / surface's pixels have the same intensity over time.

b.) Spatial Coherence:- Neighbouring points in the scene typically belong to the same surface and have typically similar motion.

c.) Temporal persistence:- The image motion of a surface patch changes gradually over time.

2.) Tracking points of constant brightness can also be viewed as the estimation of 2D paths $\bar{x}(t)$ along which intensity is conserved:

$$I(\bar{x}(t), t) = c \qquad \frac{d}{dt} I(\bar{x}(t), t) = 0$$

using Taylor series expansion / chain rule, we get:

$$\frac{d}{dt} I(\bar{x}(t), t) = \frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t}\frac{dt}{dt}$$

$$= \underbrace{\nabla I}_{\text{gradient / spatial}} \cdot \bar{v} + I_t = 0$$

→ data term

Noise:- If $I(\bar{x}, t) = I(\bar{x} + t, t+1) + n$

where n is AWGN with standard deviation σ & uncorrelated at different points.

The resulting distribution will be Gaussian with variance & mean dependent on velocity of neighbouring pixels.

3) We use first-order Taylor series approximation, since the movement across frames is small. This implies that $\Delta u, \Delta v$ are also very small.

Thus $\Delta u^2, \Delta v^2, \Delta u^3, \Delta v^3$ terms are considered to be 0.

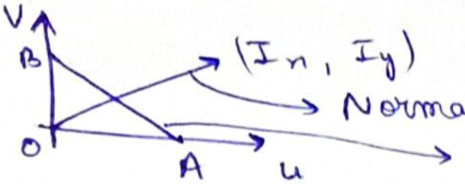
4) The optical flow constraint

$$u I_x + v I_y + I_t = 0$$

is not enough to uniquely determine the two unknowns u & v at each pixel.

For non-vanishing image gradients, it is only possible to determine the flow component parallel to $\nabla I = \begin{pmatrix} I_x \\ I_y \end{pmatrix}$, i.e., normal to image edges.

This is called Normal flow. $N_A = \dfrac{-I_t}{|\nabla I|} \dfrac{\nabla I}{|\nabla I|}$



Section 2.3

1) Optical flow in regions where local structure tensor rank is 2 implies that there is only 1 solution for the motion. A rank of 1 will mean infinte possibilities.
The threshold (γ), helps in filtering motion that are very small or may have just been noise.

2.) Yes, a different threshold helps improve the error and final optical flow output.
Different images end up requiring different threshold.

3.) A smaller window size requires a much lower threshold to give a satisfactory output. This may result in a higher number of ~~expect~~ exceptions.

A larger window size works with a higher threshold. Larger window size will lead to increase in computation time.

4.) Lucas - Kanade typically fails around rotations and occlusions, which are likely caused by objects independently moving. It cannot provide flow information in the interior of uniform images of an image.

5.) HSV color space is designed to more closely represent the human perception of color. Each channel in HSV space represents a perceptual attribute of color.

Mapping movement into HSV space helps retain more info and also understand it.