

$$C = \alpha F + (1-\alpha) B$$

C, F, B
 $\begin{cases} C = \text{pixels' composite} \\ F = \text{foreground colors} \\ B = \text{background colors} \end{cases}$
 $\left\{ \begin{array}{l} \alpha \rightarrow \text{pixels' opacity} \\ \text{component used} \\ \text{to linearly} \\ \text{blend both} \\ \text{foreground,} \\ \text{background.} \end{array} \right.$

$$\begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}_{3 \times 1} = \alpha \begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}_{3 \times 1} + (1-\alpha) \begin{bmatrix} \cdot \\ \cdot \\ \cdot \end{bmatrix}_{3 \times 1}$$

7 unknowns (alpha and three channel for F and B)

\hookrightarrow 3 eq's (one per color channel)

Impossible \Downarrow to estimate $F, B, \alpha \mid C$
 \uparrow
given

Therefore, we express this as a maximization over the probability distribution (P) ,

$$\hookrightarrow \arg \max_{F, B, \alpha} P(F, B, \alpha \mid C)$$

Bayes' Theorem:-

Likelihood: The probability of "B" being true, given "A" is true \downarrow $P(B \mid A)$
 Prior: The probability "A" being true. This is the knowledge \downarrow $P(A)$

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

\uparrow
Posterior

\uparrow marginalization:-

The probability of "A" being true, given "B" is true

The probability "B" being true

$$\arg \max_{F, B, \alpha} P(F, B, \alpha | C) = \arg \max_{F, B, \alpha} \frac{P(C | F, B, \alpha) P(F) P(B) P(\alpha)}{P(C)}$$

$$= \arg \max_{F, B, \alpha} L(C | F, B, \alpha) + L(F) + L(B) + L(\alpha)$$

~~we~~ we have to define these log likelihood terms
Now using gaussian models how,

$$L(C | F, B, \alpha) = -\frac{1}{2} \frac{\|C - \alpha F - (1 - \alpha)B\|^2}{\sigma_c^2}$$

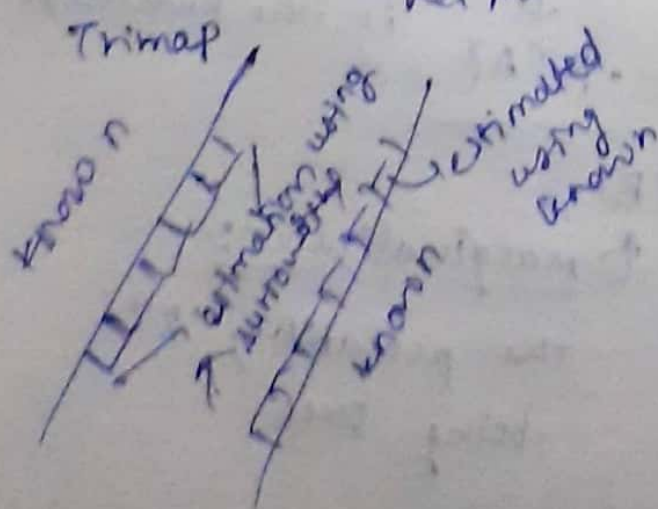
→ this log likelihood ~~term~~ shows error in measurement of C with gaussian probability distribution

where,

$$\begin{cases} \bar{C} = \alpha F + (1 - \alpha)B \\ \sigma_c = \end{cases}$$

foreground,

$L(F) \rightarrow$ we have to estimate spatial coherence of image to estimate foreground term $L(F)$.
We find colour distribution by using the known and also the previously predicted (estimated) within N pixels neighbourhood.



To robustly model

Hence total weight

$$w_i = \alpha_i^2 g_i$$

first) we weight all the pixels by α_i^2 which gives advantage to the opaque pixels of higher confidence

second) $g_i \rightarrow \sigma = 8$ to stress contribution of nearby pixels over those that are further away

for given foreground colors and the known weights $(\alpha_i^2 g_i) \rightarrow w_i$

\rightarrow we partition colors into several clusters (for clustering we use)

Orchard Bouman

for each such cluster we calculate

\bar{F} and Σ_F

$$\bar{F} = \frac{1}{W} \sum_{i \in N} w_i F_i \quad \dots (W = \sum w_i = \sum \alpha_i^2 g_i)$$

$$\Sigma_F = \frac{1}{W} \sum_{i \in N} w_i (F_i - \bar{F})(F_i - \bar{F})^T$$

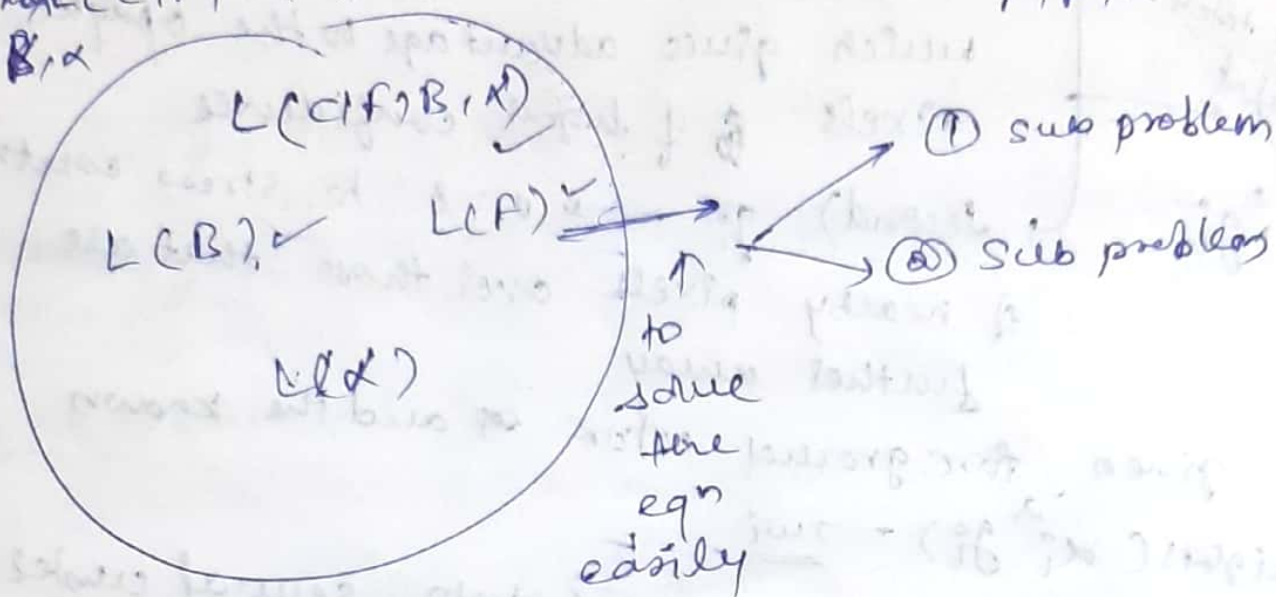
$$\text{So, } L(F) = \frac{-(F - \bar{F})^T \Sigma_F^{-1} (F - \bar{F})}{2}$$

Now for the $L(B) \rightarrow$ Background.

Analogous to the foreground, $w_i = (1 - \alpha_i)^2 g_i$

$$L(B) = \frac{-(B - \bar{B})^T \Sigma_B^{-1} (B - \bar{B})}{2}$$

$L(\alpha) \rightarrow \text{constant}$
 $\arg \min_{F, B, \alpha} L(C|F, B, \alpha) = L(F) + L(B) + L(\alpha) = \arg \min_{F, B, \alpha} P(F, B, \alpha|C)$



(1) \rightarrow assumption that α is constant.
 subproblem | take partial derivatives of eqn with respect to F and B and set them equal to zero

$$\begin{bmatrix} \Sigma_F^{-1} + \frac{1}{\sigma_c^2} & \frac{\alpha(1-\alpha)}{\sigma_c^2} \\ \frac{\alpha^2}{1-\alpha} & \Sigma_B^{-1} + \frac{\alpha(1-\alpha)^2}{\sigma_c^2} \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix}$$

$$= \begin{bmatrix} \Sigma_F^{-1} F + \frac{\alpha}{\sigma_c^2} \\ \Sigma_B^{-1} B + \frac{\alpha(1-\alpha)}{\sigma_c^2} \end{bmatrix}$$

$E \rightarrow 3 \times 3$ matrix

we can find best alpha for eqn below by solving
 6×6 linear eqn

$$\begin{bmatrix} \Sigma F + \frac{1 \times (1-\alpha)}{\sigma^2} & \frac{1 \times (1-\alpha)}{\sigma^2} \\ \frac{1 \times (1-\alpha)}{\sigma^2} & \Sigma B + \frac{1 \times (1-\alpha)}{\sigma^2} \end{bmatrix} \begin{bmatrix} F \\ B \end{bmatrix} = \begin{bmatrix} \Sigma F \bar{F} + \frac{C \times (1-\alpha)}{\sigma^2} \\ \Sigma B \bar{B} + \frac{C \times (1-\alpha)}{\sigma^2} \end{bmatrix}$$

Second problem we assume that F and B

are constant.
 observing colour C;
 in color space;

$$\alpha = \frac{(C-B)(F-B)}{\|F-B\|^2}$$

Pseudo Algorithm on lines of which code is analysed and written

① set foreground and background pixels & avoid grey
↓
calculate the unknown and known, trimap, real map. The white color in trimap is @ 100% real and the black color in trimap is 100% real. The confusion where there is grey scale in mask.

② for all pixel p marked as unknown in M_{do}
cluster foreground and background colours in $p(c)$ neighbourhood.

↓ using clustering algorithm here,
foreground and background cluster pairs do.

③ for all foreground-background cluster pairs
score for the best f, B, α using
alternative option
calculating result likelihood.

④ end for
maximal likelihood have achieved
to $F(p)$, $B(p)$, $\alpha(p)$
mark p as known

return F, B, d

Algo Bayes - Marking (C, M)

1. see foreground and background pixels in d according to m
2. for all pixels p marked in M do
cluster F, B images (colors in p 's
background)
~~cluster~~ ~~for F, B~~

for all ~~foreground-background~~ background
pixels emit

end for

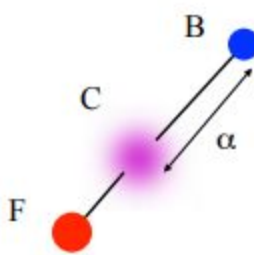
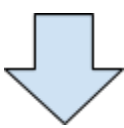
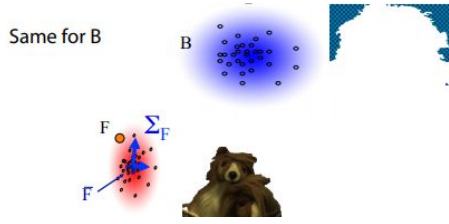
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assign to $F(p), B(p), d(p)$ results achieved
maximal likelihood.

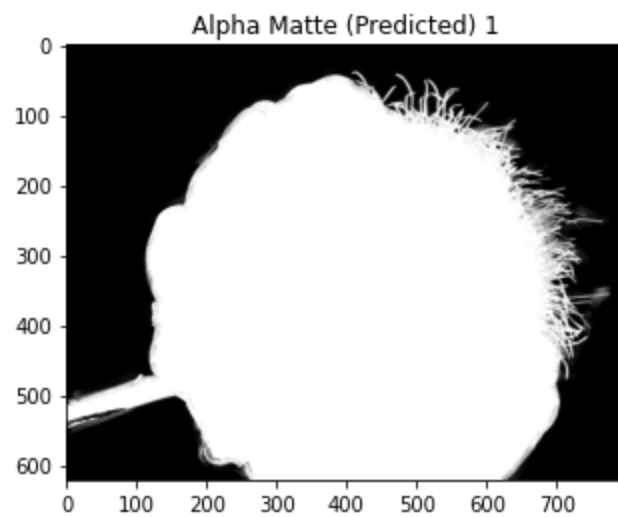
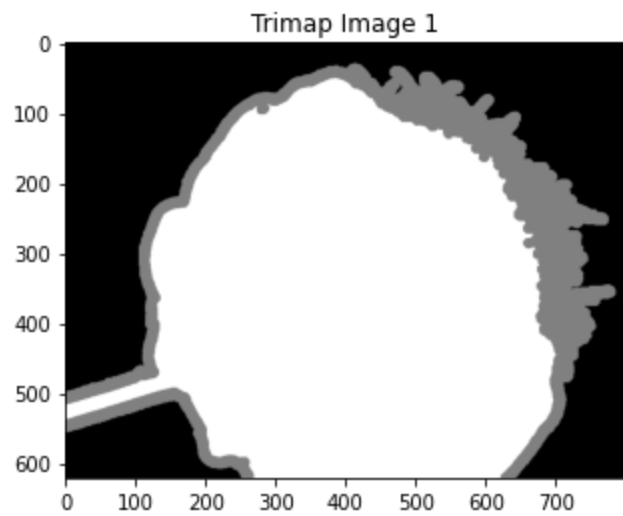
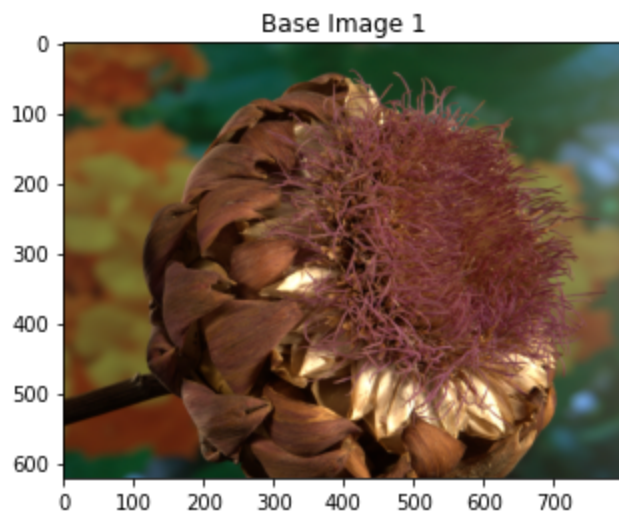
mark p as known

end for

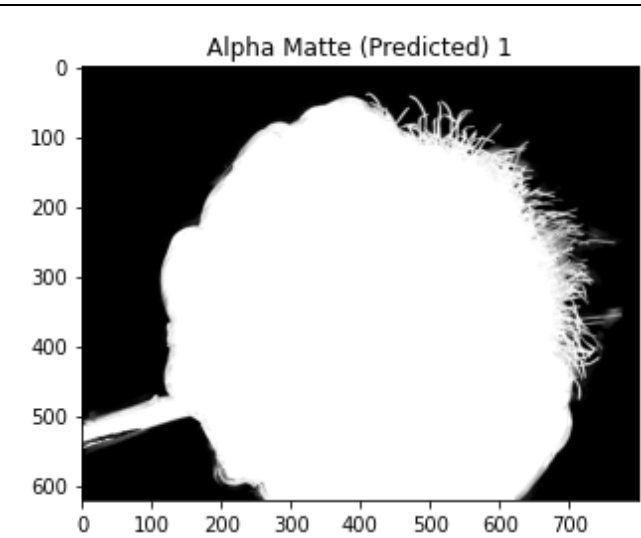
return F, B, d

L(C F,B,α)	- C - α F - (1-α) B ² / σ _C ²	
L(F)	$\bar{F} = \frac{1}{N_F} \sum F_i \quad \Sigma_F = \frac{1}{N_F} \sum (F_i - \bar{F})(F_i - \bar{F})^T$ <div style="text-align: center;">  </div> $L(F) = -(F - \bar{F})^T \Sigma_F^{-1} (F - \bar{F}) / 2$	<p>Same for B</p> 
L(B)	Similar for the B	Similar for the B

Some of the Results :



Alpha Matte (Predicted)



True Matte

