Rapid object detection

Notes CNS/CS/EE 148

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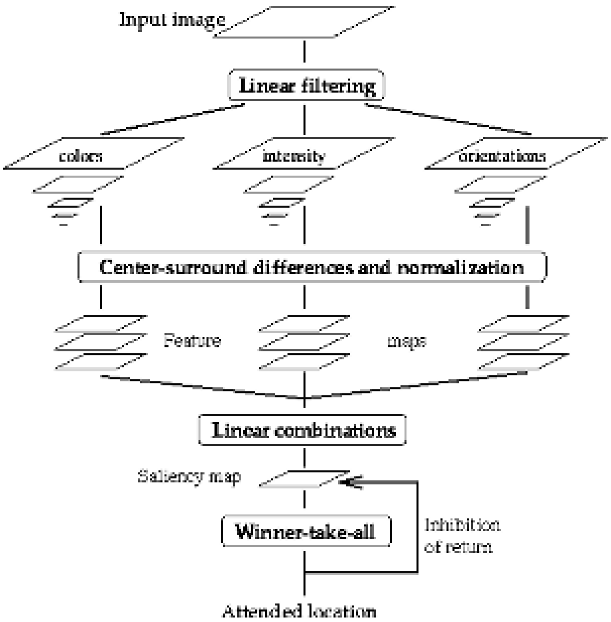
Attention

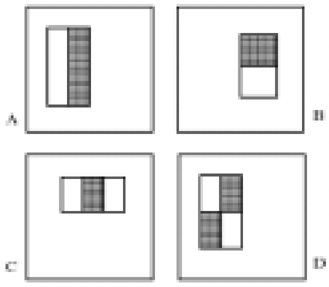
Bottom-up attention (Itti,Koch,Niebur,1998)



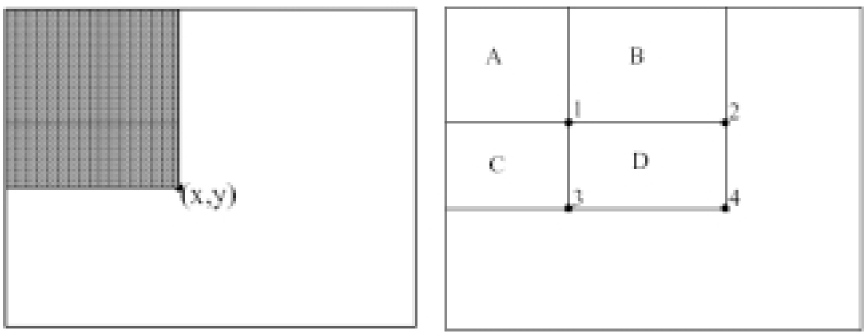
Use simple features to discard quickly large 'un-interesting' regions

Simple features (Viola,Jones)

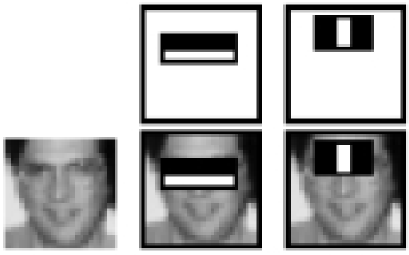
Example features - weak learners



Fast Evaluation of features - Integral Image



Result features



Too simple features

Combine the features into complex classifier

- AdaBoost

  -Linear combination of features
  -Greedy selection

- Cascade of classifiers

  -Take only high confident responses of features
  -Combine features in conjunction

AdaBoost (Freund,Schapire)

T=$\{(x_1, y_1), ..., (x_N, y_N)\}$	training set
g:R$^D \rightarrow \{-1;+1\}, \mathbf{G} = \{g\}_\alpha$	hypothesis space
$\tilde{g}(x) = \sum_{i=1}^{M} \alpha_i g_i(x)$	aggregated hypot
$\hat{g}(x) = sign(\tilde{g}(x))$	decision

Algorithm

$$w_0(n) = \frac{1}{N};$$

for i=1 to M

Find hypothesis g_i with min error ϵ_i

$$\epsilon_i = \min_\alpha \sum_{n=1}^{N} w_{i-1}(n) \frac{|y_n g_\alpha(x_n) - 1|}{2}$$

$$w_i(n) = w_{i-1}(n) \frac{(1-\epsilon_i)}{\epsilon_i} \quad if g_i(x_n) y_n = -1$$

$$w_i(n) = \frac{w_i(n)}{\sum_{k=1}^{N} w_i(k)}$$

$$\alpha_i = \log(\frac{1-\epsilon_i}{\epsilon_i})$$

Output hypothesis: $\hat{g}(x) = sign(\sum_{i=1}^{M} \alpha_i g_i(x))$

AdaBoost as gradient descent (Mason et al)

$T = \{(x_n, y_n)\}_{n=1}^{N}$, $\mathbf{G} = \{g\}_\alpha$

Assume before step m we have already selected

$G(x) = \sum_{i=1}^{m-1} \alpha_i g_i(x)$

We want to select a new function $g_m \in \mathbf{G}$ to add to the linear combination i.e. $G(x) + \alpha g_m(x)$

According to what criterion?

Define a cost functional over the lin(G) :

$C(F(x)) = \frac{1}{N} \sum_{n=1}^{N} c(F(x_n))$ $c(.)$ is a cost function

Finally we need to find:

$g_m = \arg\min_{g \in \mathbf{G}} C(G(x) + \alpha g(x))$

How to do that? ... we need a direction (function) in which out cost is minimized most

Gradient descent!

Define inner product space with

$< F, G >= \frac{1}{N}\sum_{n=1}^{N} F(x_n)G(x_n)$

$C(F(x) + f(x)) \approx C(G(x))+ < \bigtriangledown C(F(x)), \alpha f(x) >$ $\alpha > 0$

$minC(F(x) + \alpha f(x)) \Leftrightarrow min < \bigtriangledown C(F(x))\alpha f(x) >$

Concrete example C(.)= C(y G(x))

min$< \bigtriangledown C(yG(x)), g_m(x) >=$

$min\frac{1}{N}\sum_{n=1}^{N} C'(y_n G_n(x_n)) y_n g_m(x_n)$
$\Leftrightarrow max\frac{1}{Z}\sum_{n=1}^{N} C'(y_n G_n(x_n)) y_n g_m(x_n)$,
$Z = \sum_{n=1}^{N} C'(y_n G_n(x_n))$ note $Z < 0$

denote $D_n = \frac{C'(y_n G_n(x_n))}{Z}$

max $\sum_{n=1}^{N} D_n y_n g_m(x_n)$=

max $\sum_{n:y_n=g_m(x_n)} D_n - \sum_{n:y_n\neq g_m(x_n)} D_n =$

$\sum_{right} D_n - \sum_{wrong} D_n = 1 - 2\sum_{wrong} D_n$

$\Leftrightarrow min\sum_{wrong} D_n \Leftrightarrow$

min error over examples if they are taken with weights D$_n$!!!!

Finally:

Gradient descent view:

-finds the next best function in the direction of the gradient

-prescribes to assign weights over exanples

-gives way to compute the weights at each iteration

$\Rightarrow$ finding the best function is equivalent to finding the function with minimum error wrt those weights!

Assume g_m is found. How to find α ?

$\frac{dC(G(x)+\alpha g_m(x))}{d\alpha} = 0$

for AdaBoost: c(x)=e^{-x}

$\sum_{n=1}^{N} e^{-y_n G_n(x_n) - \alpha g_m(x_n) y_m} g_m(x_n) y_m = 0$

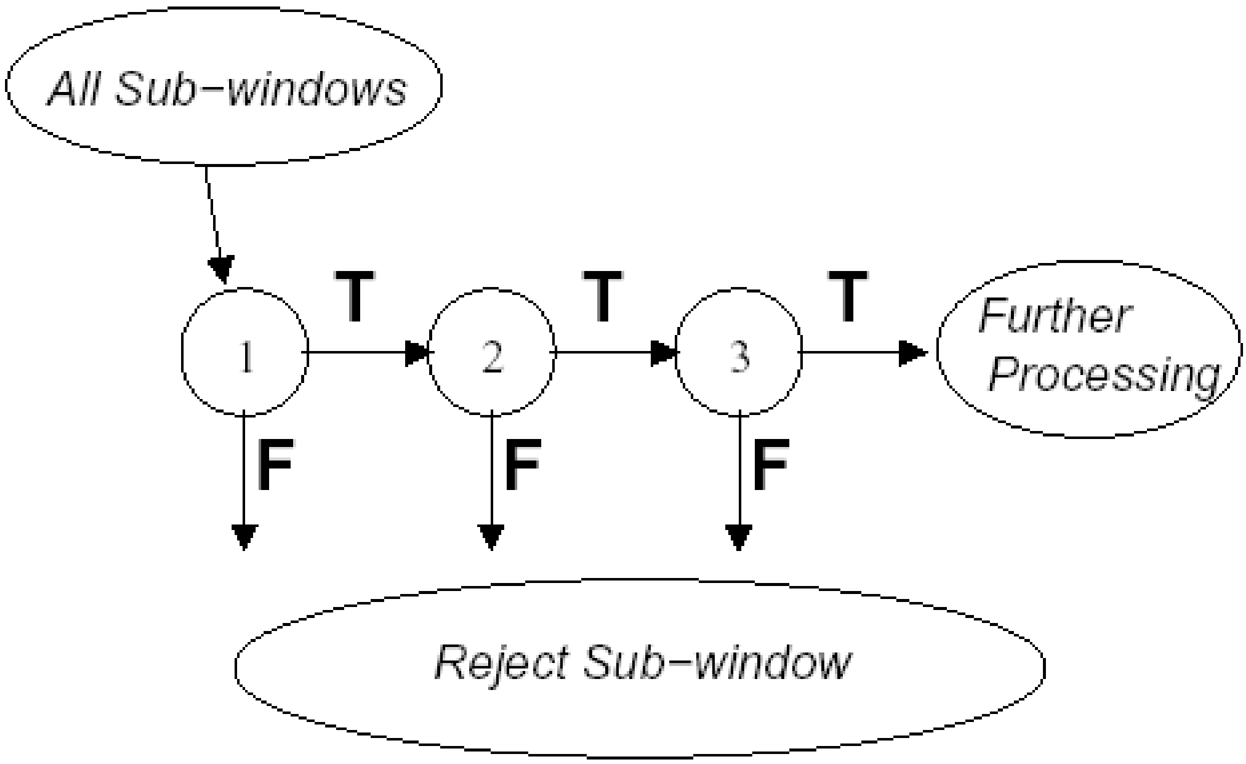
$\sum_{right} e^{-y_n G_n(x_n))} e^{-\alpha} = \sum_{wrong} e^{-y_n G_n(x_n))} e^{\alpha}$

$\alpha = \frac{1}{2} ln(\frac{\sum_{right} D_n}{\sum_{wrong} D_n}) = \frac{1}{2} log(\frac{(1-\epsilon_m)}{\epsilon_m})$

Cascade of Classifiers(Viola,Jones)

At each stage:

- if nonface,declare nonface,exit
- if face,evaluate the next stage



Rapid object detection, Viola and Jones: Outline

* Define a Hypothesis space

- Overcomplete basis of simple features

- Image preprocessed for speed optimization - Integral Image

* Algorithm: AdaBoost

- iteratively selects best weak learner

* Optimization:Cascade of AdaBoost learners

References:

Itti, Koch, Niebur, 'A Model of Saliency-Based Visual Attention for Rapid Scene Analysis',PAMI 1998;20(11):1254-1259

Freund, Schapire, 'A short introduction to boosting',Int. Joint Conf. Artif. Intel.,1999

Mason, Baxter, Bartlett, Frean, 'Boosting algorithms as gradient descent in function space',1999

Viola, Jones, 'Rapid object detection using a casacde of simple features', CVPR'2001