Simulating Human Saccadic Scanpaths on Natural Images

[1,3], C C [1], [1,2]
[1,2], F F [2,4], [2],
[1]N E . V , [2] . M P M E , P U
[3] . U , C A S , 1 4 , C
[4]D P , P U , 1 1, C
S M S , P U , 1 1, C
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Abstract

Human saccade is a dynamic process of information pursuit. Based on the principle of information maximi ation, we propose a computational model to simulate human saccadic scanpaths on natural images. he model integrates three related factors as driven forces to guide eye movements se uentially reference sensory responses, fovea-periphery resolution discrepancy, and visual working memory. For each eye movement, we compute three multi-band filter response maps as a coherent representation for the three factors. he three filter response maps are combined into multi-band residual filter response maps, on which we compute residual perceptual information (RPI) at each location. he RPI map is a dynamic saliency map varying along with eye movements. he next fixation is selected as the location with the maximal RPI value. On a natural image dataset, we compare the saccadic scanpaths generated by the proposed model and several other visual saliency-based models against human eye movement data. Experimental results demonstrate that the proposed model achieves the best prediction accuracy on both static fixation locations and dynamic scanpaths.

1. Introduction

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Proposed method

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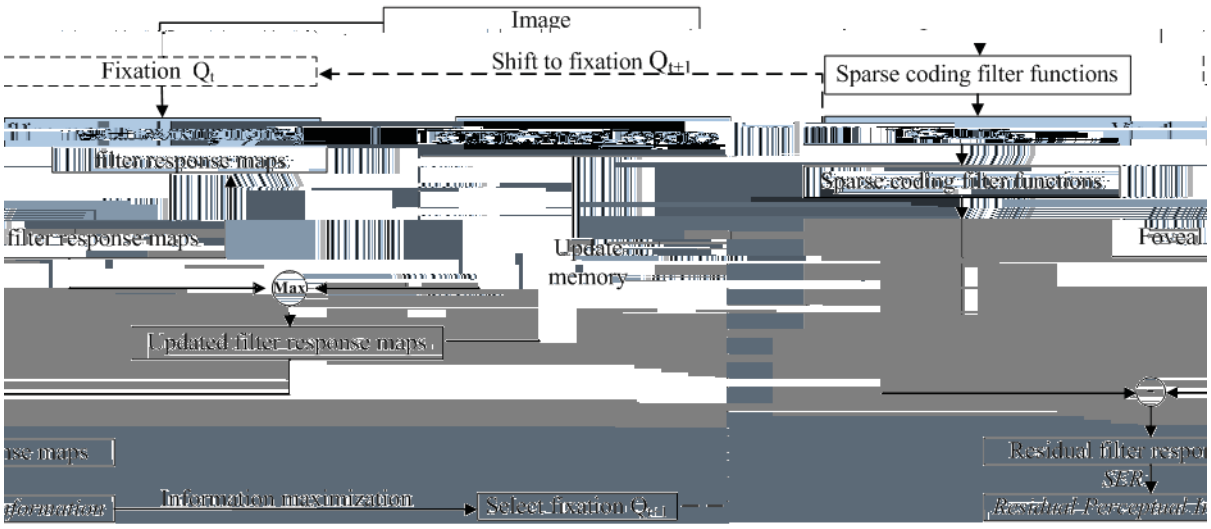
fi Q_t fi



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ϵ $0 \leq \epsilon \leq 1$.

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fi *so far*

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Site Entropy Rate 2 . fi

residual perceptual information (RPI) .

RPI

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SER fi Q_{t+1},

A , *multi-band filter response maps* ,

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1.1. Related work

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, *et al.* *self-information*

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dynamic
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2. Our Approach

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2.1. Coherent representation of three factors

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2.1.1 Sparse coding filters

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multi-band filter response maps ,
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$8 \times 8 \times 3$,
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F . 2. 4 .

2.1.2 Foveal imaging

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F . 3. A . O
F fi .

2.1.3 Visual working memory

O , fi . . V . , , , . fi . I fi . R . .

Simulating the forgetting properties. I . , . . fi ϵ $0 \leq \epsilon \leq 1$. I $\epsilon = 1$, . I $\epsilon = 0$, . I S 3.4, . . ϵ. .

Updating visual working memory. V . . fi . I . , . fi . A *Max* . . 4 . fi , $f_k^v(x,y,t)$ $f_k^w(x,y,t)$ k fi t (x,y) .

$$f_k^w(x,y,t) \leftarrow \max\left(f_k^v(x,y,t), \epsilon \cdot f_k^w(x,y,t-1)\right). \quad (1)$$

Computing residual filter response maps. fi F . 1 . P . A . , . fi . fi $r_k = |f_k^o - f_k^w|$, f_k^o k .

2.2. Measuring residual perceptual information

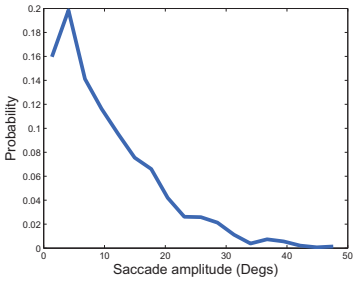
F , . fi . I . , . *Site Entropy Rate* SER 2 . fi . *Site Entropy Rate* fi . R . I , . fi . SER . . SER , SER i

$$S_i = \sum_k SER_{ki} = -\sum_k (\pi_{ki} \sum_j P_{kij} \log P_{kij}) \quad (2)$$

π_{ki} i k fi , P_{kij} i j k fi . A 2 , SER . , . P 2 . SER . SER . . F , SER . . fi . M , fi , *e.g.*, , . . S , . . SER . . , . . .

2.3. Saccadic amplitude

U . , . F . 4. I . 90% . 20° . . fi . , , fi Q_{t+1} . fi Q_t. F , $Z \times Z$. fi Q_t , . $Z/2$. 4 20° . . SER .



F . 4. . . .

Q_{t+1}. N , Q_{t+1} $p(z \leq Z/2)$,

F . 4.
A fi Q_{t+1}, .

3. Experimental Results

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3.1. Dataset and eye movement data collection

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3 1 . A
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3.2. Evaluation of fixation order

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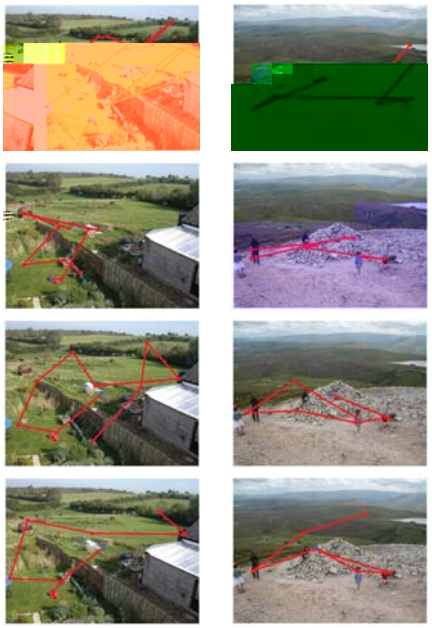

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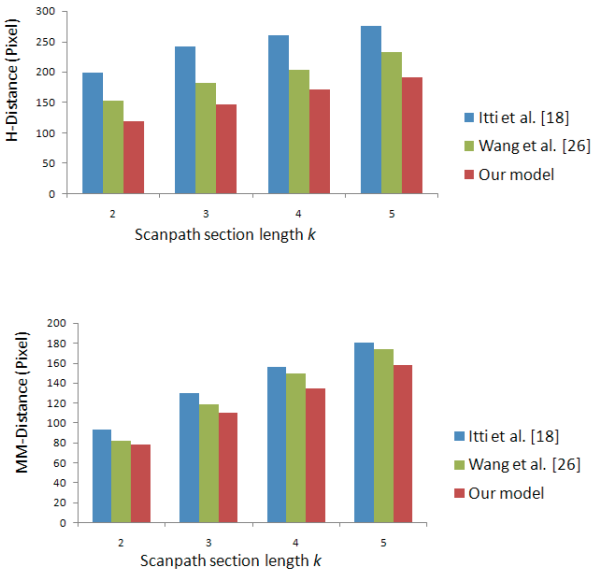

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‹ k.

3.2.1 Distance of scanpaths

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time-delay embedding, .
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‹ k, . . $C_m^k(t)$ =
$(c_m(t), \cdots c_m(t+k-1))$ k
, t fi
m. t,
‹ . k
$X = \{C_m^k(t)\}_t \subseteq \mathbb{R}^k$. S
$Y = \{C_h^k(\tau)\}_\tau$ k
‹ . I .
$k = 2$,
fi . C . . X Y
$\mathbb{R}^k$ 4
. .
F k $x =$
$C_m^k(t) \in X$, fi .
$d_k(x, Y) = \min_\tau\{\|x - C_h^k(\tau)\|_2\}/k$. I
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‹ . k , $d_k(x, Y)$
x. ,
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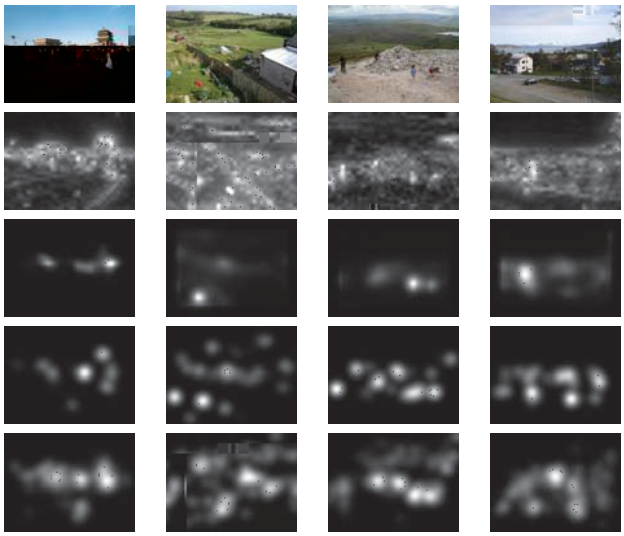

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$$d_H^k = \max_t\{\min_\tau\{\|C_m^k(t) - C_h^k(\tau)\|_2\}\}/k \quad 3$$
$$= \max_t\{d_k(C_m^k(t), Y)\}. \quad 4$$

mean minimal distance MM D ,
, fi $d_M^k = \mathsf{E}_t[d_k(C_m^k(t), Y)]$.
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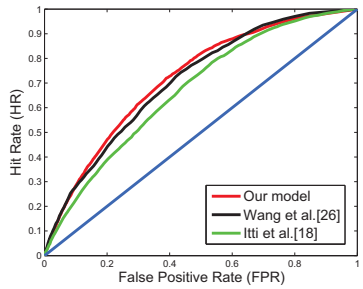
‹ ‹ ‹ $\epsilon = 0.7$,
$Z = 800$, ‹ . ‹ ‹
2.3°. F .



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1. ROC

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3.4. Assessment of the forgetting factor

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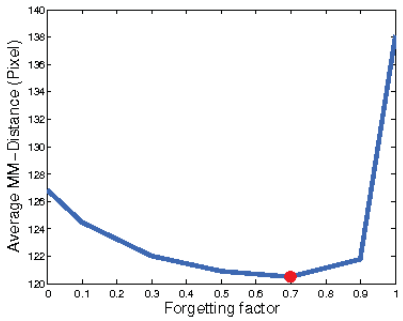

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4. Conclusion, Discussion and Future Work

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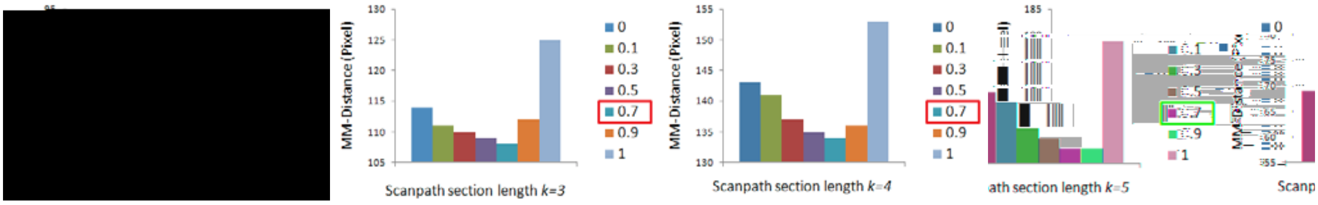

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D. , V. M , N. V . NIPS, 2 .

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Acknowledgments

N S F . C . N . 2 12 2 , N R 3 P C . N . 2 C 32 4.

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