Positioning accuracy optimization of driver fatigue detection projection location algorithm

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Abstract

As the standard scheme - still algorithm has the problems of bad convergence and low accuracy in the human eye detection, this paper puts forward a driver's eye detection positioning model based on SURF measure optimization Mean-shift algorithm. Making square wave filter and image convolution as an approximation to substitute Hessian matrix resolution, then inputs the image function and Gaussian function convolution to execute the second sampling repeatedly, and then builds the image scale space based on SURF pyramid structure, finally, introduces the built scale space and uses the weighted direction histogram to describe the target model in order to strengthen the robustness of the Mean-shift algorithm. Simulation experiment shows that the SURF feature measurement optimization

improves the convergence of the improved Mean-shift algorithm greatly, and the proposed driver's eye detection positioning model based on SURF measurement optimization Mean-shift algorithm has a good performance, whose accuracy is better than standard Mean-shift algorithm.
Key words: FATIGUE DRIVING, EYE LOCATION, MEAN-SHIFT ALGORITHM, SURF ALGORITHM

Introduction

Fatigue driving refers to the driver after driving for a long time, driving is instability which is caused by the physiological and psychological function serious decline, the phenomenon could lead to the occurrence of traffic accident [1].Like drunk driving, fatigue driving should be more and more get the attention of people, it bring disastrous consequences are unpredictable and imagination, and fatigue driving immeasurably stronger, fatigue driving will be more difficult to judge [2].Above all, fatigue driving social harm is very large, both in human and material resources can cause different degree of loss, therefore, the research of driver fatigue detection method is a very significant meaning.

Along with the progress of the Times, and the booming development of the sensor technology, computer vision and data analysis technology, fatigue detection research domain constantly emerges new evaluation methods and standards. Kithil through real-time monitoring the driver's head position, according to the coordinate changing of head to judge whether drivers have sleep, the experiment verified the head displacement can better reflect the driver in the process of driving sleepy phenomenon [3].The head displacement sensor developed by ASCI (Advanced Safety Concepts Inc.) is a cascade capacitance sensor which is installed at the top of the cab, through each sensor sensing target spacing to achieve the purpose of head accurate positioning coordinates and head tracking head position, using the head coordinate changes in a specific time period to reflect the driver whether going to sleep[4]. Rongben Wang using skin color segmentation, the classification of the Fisher and regional analysis location mouth, and through the Kalman filter to track of mouth, extracting mouth contour feature to constitute feature vector, eventually using BP neural network to make sure mouth state for fatigue detecting[5]. Qun Wu etc. measure the ECG and PERCLOS value of drivers in the different level of fatigue, comprehensive analysis two aspects of data, eventually realize the characteristics testing of fatigue driving[6]. Zhu Shuliang etc. use information fusion technology, use the road structure, driving track and PERCLOS principle to establish data structure relations between single detection characteristic and driver fatigue, it is concluded that the minimum decision algorithm are optimized by the algorithm, which can determine the driver's fatigue [7].Zhi-chun li uses fuzzy neural network technology to do data fusion for PERCLOS, eyes closing velocity, nodding frequency, yawning frequency etc. multiple fatigue characteristic parameters, found the new standard of fatigue state test [8]. Li curtain research using the cumulative difference and Hough transform etc. real-time image processing technology to track eyes, analysis eyes' state, extract eyes' characteristic parameters, calculate the PERCLOS value to determine fatigue degree, he completed the combination of software development and DSP hardware [9].Lough borough maked a comprehensive evaluation by introducing the reference coefficient, including vehicle driving condition, the continuous driving time of driver and so on, if detected the fatigue signs of driver, it would making alarm through sound and image [10].

According to the convergence defect of Mean-shift algorithm, this paper proposes a driver's eye detection positioning model based on SURF measure optimization Mean-shift algorithm, and simulation experiment is carried out to verify the validity of the model.

The convergence analysis of Mean-shift algorithm

Mean-shift algorithm is a kind of smooth and no arguments density estimation technique, it is one of the most common no arguments density estimation methods, kernel density estimation is one of the most common density estimation function. In d dimensional space R^d on the data $x_i, i = 1, 2, ..., n$ for given group n, multiple nuclear function $K(x)$ and a $d \times d$ symmetric positive definite matrices H, density with the formula given in the x:

$$\hat{f}(X) = \frac{1}{n}\sum_{i=1}^{n} K_H(X - X_i) \quad (1)$$

Among them

$$K_H(x) = |H|^{-1/2} K(H^{-1/2}x) \quad (2)$$

Among them $K()$ is a kernel function. Kernel function must be about the y axial symmetry. It usually has the nature of symmetry, and is integral to 1, $\int_R K(x)dx = 1$, the density of kernel function $K()$ is a weight function.

Kernel density estimation can also be extended to the multidimensional space and multiple kernel function $K()$ is by product of univariate kernel function:

$$K^P(x) = \prod_{i=1}^{d} K_1(x) \quad (3)$$

$$K^S(x) = a_{k,d} K_1(\|x\|) \quad (4)$$

Here the multivariable kernel function $K^P(x)$ get by product of radial basis $K(x)$; and $K^S(x)$ through the single variable kernel function in the rotation of the d dimensional space, with a fixed radius, the value of the function are the same, namely $K^S(x)$ is radial symmetry; Constant term $a_{k,d}$ ensure that $K^S(x)$ value of 1 in the plane of integral.

Radial symmetric kernel function achieve the conditions for:

$$K(x) = c_{k,d} k(\|x\|)^2 \quad (5)$$

Because of all the location of the parametric matrix H said it would greatly increase the complexity of the problem, so in practice, the matrix H is often simplified as a diagonal matrix $H = diag[h_1^2, ..., h_d^2]$ or more directly $H = h^2 I$. The latter obviously benefits is to make the parameters into a value $h > 0$, reducing the complexity of the problem again. In this way, H plug in to the equation (2), can get kernel function equation. In the kernel function equation to (1), can be multidimensional kernel density estimation which can be represented as:

$$\hat{f}(X) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{X - X_i}{h}\right) \quad (6)$$

If the radial symmetric kernel functions meet the conditions of (6) in the type, the density estimation expressions is written based on the outline of nuclear density function, there are :

$$\hat{f}_{h,K}(X) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n} k\left\|\frac{X - X_i}{h}\right\|^2 \quad (7)$$

Formula (7) is Mean-Shift algorithm for calculating eigenvalues probability density commonly used formula.

The convergence of Mean-shift algorithm determine whether the core of the remote sensing image segmentation are accurate, convergence of Mean - shift and the increasing of the value of equivalent to prove proposition: If the kernel function is a concave function $k(x)$ of decreasing defined, then descending convergent sequence $\{y_j\}_{j=1,2}$ and $\{\hat{f}_{h,K}(j)\}$.

Because n is limited, series $\{\hat{f}_{h,K}(j)\}$ is bounded, according to the definition of series $\{\hat{f}_{h,K}(j)\}$:

$$\{\hat{f}_{h,K}(j)\} - \hat{f}_{h,K}(j) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n}\left[k\left\|\frac{y_{j+1} - x_i}{h}\right\|^2 - k\left\|\frac{y_j - x_i}{h}\right\|^2\right]$$

(8)

Based on the definition of concave function, for all of $x_1, x_2 \in [0, \infty)$, $x_1 \neq x_2$ is

$$k(x_2) \geq k(x_1) + k'(x_2)(x_2 - x_1) \quad (9)$$

Because $g(x) = -k'(x)$, (9) can be turned into

$$k(x_2) - k(x_1) \geq +g(x_1)(x_1 - x_2) \quad (10)$$

On the plug type to (8), get

$$\begin{aligned}
&\hat{f}_{h,K}(j+1) - \hat{f}_{h,K}(j) \\
&\geq \frac{c_{k,d}}{nh^{d+2}}\sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2 \left[\|y_j - x_i\|^2 - \|y_{j+1} - x_i\|^2\right] \quad (11) \\
&= \frac{c_{k,d}}{nh^{d+2}}\sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2 \left[\|y_j\|^2 + 2(y_{j+1}^T - y_j^T)x_i - \|y_{j+1}\|^2\right]
\end{aligned}$$

Get:

$$\hat{f}_{h,K}(j+1) - \hat{f}_{h,K}(j) \geq \frac{c_{k,d}}{nh^{d+2}}\|y_{j+1} - y_j\|^2 \sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2 \quad (12)$$

Because $k(x)$ is monotone decreasing at $x \geq 0$, so $\sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2$ is an arithmetic number. If $y_{j+1} \neq y_i$, the right of equation (12) is a strictly positive real number. thus it can be seen $\{\hat{f}_{h,K}(j)\}$ is an increasing sequence. Since it is bounded, it is a convergent sequence.

Then accumulate m item of equation (12), then

$$\begin{aligned}
\hat{f}_{h,K}(j+m) - \hat{f}_{h,K}(j) &\geq \frac{c_{k,d}}{nh^{d+2}}\|y_{j+m} - y_{j+m-1}\|^2 \sum_{i=1}^{n} g\left\|\frac{y_{j+m-1} - x_i}{h}\right\|^2 \\
&\quad + ... + \frac{c_{k,d}}{nh^{d+2}}\|y_{j+1} - y_j\|^2 \sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2 \\
&\geq \frac{c_{k,d}}{nh^{d+2}}\left[\|y_{j+m} - y_{j+m-1}\|^2 + ... + \|y_{j+1} - y_j\|^2\right] M \\
&\geq \frac{c_{k,d}}{nh^{d+2}}\|y_{j+m} - y_j\|^2 M
\end{aligned}$$

(13)

M is the minimum value of $m\sum_{i=1}^{n} g\left\|\frac{y_j - x_i}{h}\right\|^2$. thus it can be seen $\{y_j\}_{j=1,2}$ is a Cauchy sequence, $\{y_j\}_{j=1,2}$ is also convergence. The theorem ensures the convergence of Mean - shift and the increasing of the value.

From the point of view of mathematics, Mean-shift method and Newton climbing method are similar, it is a kind of geting maximum function based on the gradient method. So, Mean-shift in the driver's eye detection, there is a certain error.

Mean-shift algorithm based on the characteristics of SURF measurements

SURF detection algorithm is determined by the Hessian matrix, the matrix H is given below:

$$H(X,t)=\begin{bmatrix} L_{xx}(X,t) & L_{xy}(X,t) \\ L_{xy}(X,t) & L_{yy}(X,t) \end{bmatrix} \quad (14)$$

$$L(X,t)=G(t)*I(X) \quad (15)$$

$L_{xx}(X,t)$ is the representation of an image under the different resolution, which can take advantage of the convolution of gaussian kernel $G(t)$ and image function $I(X)$ at point $X=(x,y)$, kernel function $G(t)$ specific said such as type (16), $g(t)$ for gaussian function, t for gaussian variance, L_{yy} and L_{xy} in the same way.

In this way each pixel in the image can calculate The decision of the determinant value H, and use this value to distinguish the point of interest. For the convenience of application, using square wave filter and image convolution as approximation D_{xx} instead of L_{xx}, to balance the accurate value and the approximation error is introduced into weight w, weight w changes with scales, and discriminant matrix H can be expressed as:

$$G(t)=\frac{\partial^2 g(t)}{\partial x^2} \quad (16)$$

$$\det(H_{approx})=D_{xx}D_{xy}-(wD_{xy})^2 \quad (17)$$

The scale of the image space is the representation of the image under the different resolution, by type (15) we can know that an image, $I(X)$ said in different resolution can be done using the gaussian kernel $G(t)$ convolution, the scale of the image size is generally represented by gaussian standard deviation $\sigma(\sigma=t^{1/2})$.

In the field of computational vision, scale space is regarded as a symbolic expression of image pyramid, among them, the function of the input image with gaussian function repeatedly nuclear convolution and repeatedly on the second sampling,which is mainly used to the implementation of SIFT algorithm. But each layer image depends on the previous image, and the size of image need to reset. Therefore, the calculation method for computing is larger, and SURF algorithm increases the size of the image, which is also the difference of SIFT algorithm and SURF algorithm in the application of using pyramid principle.

Algorithm allows the scale space of multilayer is processed at the same time, and don't need to secondary sampling of images, so that the algorithm performance improvement. Fig 1 is a traditional way to build a pyramid structure as shown in the image. The size of the image is changed, and the operation will be repeatedly used pair gaussian function layer for smoothing, Fig 2 using SURF algorithm to build the pyramid structure, the original image unchanged and only the filter size changed.

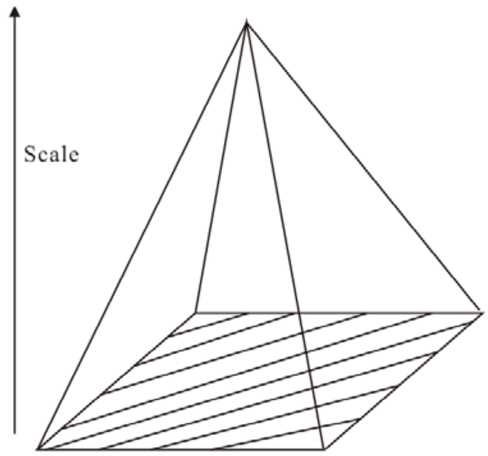

Figure 1. Traditional pyramid structure

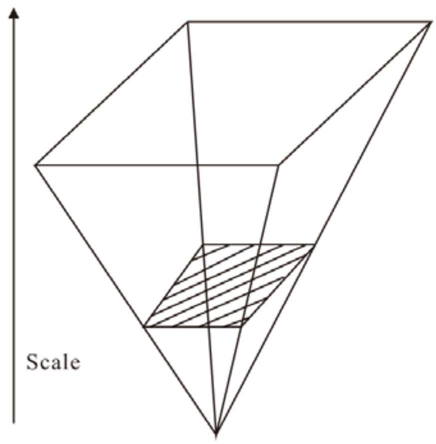

Figure 2. SURF algorithm pyramid structure

To enhance the robustness of the Mean-shift algorithm, this paper adopts weighted direction histogram to describe the target model, the specific calculation formula is as follows

$$\hat{H}_t(x_0) = \hat{C}\sum_{i=1}^{\hat{N}}\sum_{j=1}^{\hat{K}} k\left(\left\|\frac{x_{ij}-x_0}{\hat{r}}\right\|^2\right)\delta(\theta(x_{ij})-t) \qquad (18)$$

Among this formula, x_{ij} is the j the coordinates of a pixel of the i feature points , $\theta(x_{ij})$ is the pixel points in the direction of the vector, x_0 is the target model center coordinates, $\hat{N}$ is the number of feature points, $\hat{K}$ is the number of pixels in the each neighborhood, $\hat{r}$ is the radius of the template, $k(x)$ is the weighted kernel function, making the nearer the center of the target model of pixels to get the weight value, the greater the smaller conversely. $\hat{C}$ is the normalized constant, $\delta(x)$ is the shock function. Specific expression is as follows:

$$\hat{C} = \frac{1}{\sum_{i=1}^{\hat{N}}\sum_{j=1}^{\hat{K}} k\left(\left\|\frac{x_{ij}-x_0}{\hat{r}}\right\|^2\right)} \qquad (19)$$

$$\delta(\theta(x_{ij})-t) = \begin{cases} 0, \theta(x_{ij}) \neq t \\ 1, \theta(x_{ij}) = t \end{cases} \qquad (20)$$

Location y model can be described as a candidate target:

$$H_t(y) = C\sum_{i=1}^{N}\sum_{j=1}^{K} k\left(\left\|\frac{x_{ij}-y}{r}\right\|^2\right)\delta(\theta(x_{ij})-t) \qquad (21)$$

By above knowable, target tracking problem can be simplified to find the most optimal y to $H_t(y)$ and $\hat{H}_t(x_0)$, Bhattacharrya coefficient $\rho(y)$ as the similarity measure between the two distribution, namely:

$$\rho(y) = \rho[h(y), \hat{h}(x_0)] = \sum_{t=1}^{T}\sqrt{H_t(y)\hat{H}_t(x_0)} \qquad (22)$$

Taylor expansion to type in y_0 place get Bhattacharyya coefficient approximation formula:

$$\rho(y) \approx \frac{1}{2}\sum_{t=1}^{T}\sqrt{H_t(y)\hat{H}_t(x_0)} + \frac{C}{2}\sum_{i=1}^{N}\sum_{j=1}^{K} w(x_{ij})k\left(\left\|\frac{x_{ij}-y}{r}\right\|^2\right)$$

(23)

Among them

$$w(x_{ij}) = \sum_{t=1}^{T}\delta[\theta(x_{ij})-t]\sqrt{\frac{\hat{H}_t(x_0)}{H_t(y_0)}} \qquad (24)$$

Obviously, type the first item is a constant term in (24), to make $\rho(y)$ maximum, only need to consider the second term, so it can use Mean - Shift algorithm to the iterative optimization to locate the Position of the next target.

Algorithm performance simulation

In order to verify the performance of the improved algorithm proposed in this paper, we do the simulation experiment on it. First of all, do the convergence of the simulation on Mean-shift algorithm and the improved Mean-shift algorithm proposed in this paper ,the results shown in figure below.

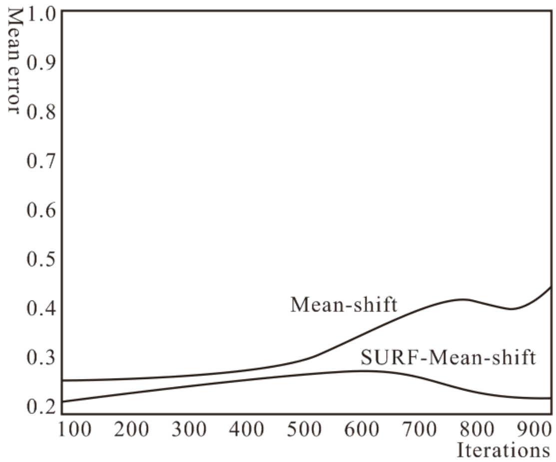

Figure 3. Mean-shift algorithm to improve the convergence of simulation

Then, using the standard Mean shift algorithm and improved algorithm proposed in this paper do the performance of the driver's eye detection simulation, the results shown in figure below.

Figure 4. Driver eye detection algorithm standard positioning results

Figure 5. Improved algorithm of driver eye detection positioning results

From the above results we can know that the optimization of SURF feature measure greatly improves the convergence of the improved Mean-shift algorithm proposed in this paper. And the improved Mean-shift algorithm based on SURF measurement of driver eye detection positioning model is at good performance. Its accuracy is better than standard Mean- shift algorithm.

Conclusion

According to the traffic accident statistical yearbook: worldwide, more than 30% of road traffic accident and about 15-20% of railway traffic accidents are related with fatigue driving, and fatigue driving will seriously affect the driver's alertness, complaisance and safe driving ability. This paper proposes a optimization scheme based on SURF measure algorithm of driver eye detection - shift positioning model, solving the problem of Mean-shift algorithm’s convergence. The experimental simulation results show that the optimization of SURF feature measurement greatly improving the convergence of the improved Mean-shift algorithm. And the improved Mean-shift algorithm based on SURF measurement of driver eye detection positioning model is at good performance. Its accuracy is better than standard Mean- shift algorithm.

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