Sports Learning Mixed Model Facing Feature Marking

Qingshuang Guo
School of Physical Education, Jiujiang University, Jiujiang, 332005, China

Abstract
The feature marking has gradually become a new research hotspot in the sports world. Aiming at the problems such as low scientific feature, weak real-time performance etc. in the current motion feature marking learning, this paper proposes a motion learning mixed model method facing feature marking. Firstly, it collects the information of athletic students, by use of mixed learning model does specific learning on the athletic students, by use of the mean shift algorithm marks features of each sports student, and finally, uses VC6.0++ to realize the motion feature marking simulation experiment. The results show that this paper improves the precision of the feature marking of sports students, and accelerates the speed of motion feature marking, and for the sports students having good robustness under conditioning of sheltering and scene changing, it has better performance than other current motion feature marking algorithm and holds higher practical application value.

Keywords: Mixed Learning Algorithm, Feature Marking, Mean Shift Algorithm, Simulation Experiment.

1. INTRODUCTION
Feature marking is a hotspot in computer vision research. It is based on the correct access to the feature marking. Literature (Hasan, and Roy-Chowdhury, 2015) defines that when there are multiple targets in a field of view, it is necessary to be able to obtain and distinguish the features of each target. After the image is binarized, the target region of the binary image is made a pixel marking to distinguish the different targets so to extract the features of each target. In Literature (Bai, Chen, Xie, and Li, 2016), the feature marking is based on the marking, so the establishment of high-precision feature marking algorithm is still facing great challenges.

There are many motion feature marking algorithms, the traditional motion feature marking algorithm is the Kalman filter algorithm. In literature (Chang, Abdul-Kareem, Merican, and Zain, 2013) it realizes the motion feature marking according to the mean vector and the covariance matrix and believes the target is a linear motion model. When the target appears non-linear movement under the influence of external factors, the precision of motion feature marking is low. The based-on particle filter motion feature marking algorithm in the literature (Jacksowski, Krawczyk, and Wozniak, 2014) can do accurate feature marking of the track of the non-linear motion target, feature marking results are better than the Kalman filter algorithm, but it is easy to have particle degeneracy phenomenon and have poor universality. In literature (Jiang, Liu, and Song, 2017) aiming at the problems such as scene changing, sheltering etc. it proposes a motion feature marking algorithm for multi-sample learning, and it has good robustness, but it cannot do precise feature marking again when the target disappears and appears again. In literature (Tong, and Schierz, 2011) the Mean shift (MS) algorithm is a kind of motion feature marking algorithm which has appeared in recent years. It has quick tracking speed and strong robustness. But when the target is seriously sheltered or swiftly moving, the target is easy to lose and is unable to predict the achievements of the sports students so the precision of the feature marking shall be improved. Literature (Klimczyk, and Klimczyk, 2015) proposes a video feature marking algorithm for wireless sensor node collaboration, and combining with the Kalman filter algorithm to predict the target track and achieve video feature marking, but it does not take into account the energy consumption of the sensor nodes.

In order to improve the accuracy and real-time of motion feature marking, this paper studies and analyzes several kinds of marking algorithms, points out some shortcomings in the algorithms and gives the improved feature marking algorithms, which not only greatly simplifies the design of program algorithms. The Mean shift (MS) algorithm does feature marking on the targets and realizes real-time dynamic feature marking on the sports students. The experiment shows that compared with the traditional motion feature marking algorithms this method improves the precision of the motion feature marking and has better performance of the feature marking than other algorithms, thus verifies the effectiveness of the algorithm.

2. RELATED THEORY
2.1. Single Learning Feature Modeling
For the pixel point \((x, y)\) at t moment, there is

\[
p(I(x, y, t) = \eta(x, \mu_t, \sigma_t)) = \frac{1}{\sqrt{2\pi\sigma_t}} \exp\left(-\frac{(I - \mu_t)^2}{2\sigma_t}\right)
\]

(1)
Where: \( \eta \) represents the learning probability density function, \( \mu \) and \( \sigma \) represents the mean vector and the standard deviation, respectively.

If the image has \( N \) frames, then the expected value and deviation of the initial feature model of the pixel \((x, y)\) are

\[
\mu_0(x, y) = \frac{1}{N} \sum_{i=0}^{N-1} I(x, y, t) \\
\sigma_0(x, y) = \sqrt{\frac{1}{N} \sum_{i=0}^{N-1} [I(x, y, t) - \mu_0((x, y))]}
\]

At \( t \) moment, the gray value of the pixel \((x, y)\) is judged according to formula (4)

\[
output(x, y, t) = \begin{cases} 0 & \text{if } \text{condition} \text{ is satisfied} \\ 1 & \text{otherwise} \end{cases}
\]

Where: \( T_p \) indicates the probability threshold.

The feature model is updated for the pixel to be determined as a feature, specifically

\[
\mu_i(x, y) = (1 - \alpha) \mu_i(x, y) + \alpha \times I(x, y, t) \\
\sigma_i^2(x, y) = ((1 - \alpha) \sigma_i^2(x, y) + \alpha \times I(x, y, t) - \mu_i(x, y))^2
\]

Where: \( \alpha \) represents learning factor.

2.2. Mixed Learning Model

The definition of mixed learning model in the literature (Peng, 2015) is a classical model of motion target detection, which is based on the single learning model, and can use multiple single learning functions to express complex and varied scene features, and has good treatment results for the problems such as scene changing, sheltering etc. The main work steps are: matching learning mode selection, model updates and feature display.

With \( K \) learning distributions, the learning model feature for the pixel \((x, y)\) at \( t \) moment is

\[
\eta(I(x, y, t)) = \sum_{i=1}^{K} \omega_i \eta_i(I(t), \mu_i', \sigma_i')
\]

where: \( \omega_i \) represents the weight of the learning distribution.

According to the \( \omega_i/\sigma \) value sort \( K \) learning distribution, select the former \( B \) learning distribution as a feature, the rest of the learning distribution is updated, where the former \( B \) learning distribution is considered a feature model, they meet the following conditions

\[
B = a \arg \min \left\{ \sum_{i=1}^{K} \omega_i > T \right\}
\]

where \( T \) represents the prior probability of the pixel being determined as a feature.

2.3. The Working Steps of The Mixed Learning Model

Feature pixel matching

Match the gray value \((x,y,t)\) of the pixel point \((x, y)\) at \( t \) moment with the No. \( m \) learning distribution. If the formula (9) is satisfied, then the matching is successful, the pixel point \((x, y)\) should be featured.

\[
\|I(x, y, t) - \mu_m'\|_2 < \beta \cdot \sigma_m'
\]

Where: \( \beta \) represents the multiple of the \( \lambda \) standard deviation.

Feature update

If the pixel point \((x, y)\) matches successfully, update the mean and variance of its learning distribution

\[
\mu_i^{t+1} = (1 - \beta) \mu_i + \beta \times I(t+1) \\
(\sigma_i^{t+1})^2 = (1 - \beta) (\sigma_i^2)^2 + \beta \times (I(t+1) - \mu_i)^T (I(t+1) - \mu_i^{t+1})
\]

Where: \( \beta \) is the update rate. Its definition is as follows

\[
\beta = \alpha \cdot \eta(I(t), \mu_i, \sigma_i)
\]

Where the parameter \( \alpha \) is similar to the corresponding parameter in the single learning feature model, called the learning rate.

In the \( t+1 \) moment, the weight update way is

\[
\omega_i^{t+1} = (1 - \alpha) \omega_i + \alpha \cdot D_i' (i \leq K)
\]

If the learning distribution matches the current pixel, \( D_i' = 1 \), otherwise \( D_i' = 0 \).
2.4. MS Algorithm

The Mean shift (S) algorithm proposed in the literature (Langdon, Harris, Burdette, and Rothberger, 2015) is an excellent feature marking algorithm. The bin-bin color histogram is used to represent the target. The target center is $x_0$, the pixel in the feature marking target box is $\{x_1, x_2, \ldots, x_N\}$. $N$ represents the number of pixels within the box, the color histogram is:

$$q_n = C \sum_{i=1}^{N} k \left( \left\| \frac{x_i - x_0}{h} \right\| \right) \delta(b(x_i) - u)$$

(14)

Where: $k(x)$ is a kernel function; $\delta(x)$ is the unit step function; $b(x)$ describes the relationship between RGB and bin space mapping.

The normalized constant coefficient $C$ of the target model is calculated as follows

$$C = \frac{1}{\sum_{i=1}^{N} k \left( \left\| \frac{x_i - x_0}{h} \right\| \right)}$$

(15)

The pixel sequence in the candidate target box is $\{y_1, y_2, \ldots, y_N\}$, that the target center is $y_0$, the color histogram of the candidate target is

$$p_n = C \sum_{i=1}^{N} k \left( \left\| \frac{y_i - y_0}{h} \right\| \right) \delta(b(y_i) - u)$$

(16)

The normalized constant coefficient $C_s$ of the candidate model is calculated as follows

$$C_s = \frac{1}{\sum_{i=1}^{N} k \left( \left\| \frac{y_i - y_0}{h} \right\| \right)}$$

(17)

Set $\{x_i\}_{i=1,2,\ldots,n}$ the position vector set of the target pixel, then the $x$ kernel function density estimation formula is

$$\hat{f}(x) = \frac{1}{nh^2} \sum_{i=1}^{n} k \left( \left\| \frac{x - x_i}{h} \right\| \right)$$

(18)

Where: $k(x)$ is the kernel function, $h$ for the nuclear radius (Hasan, and Roy-Chowdhury, 2015; Bai, Chen, Xie, and Li, 2016).

$$K_h(x) = \begin{cases} \frac{1}{2} C_d (d+2)(1-\left\| x \right\|^2) & \left\| x \right\| < 1 \\ 0 & \left\| x \right\| \geq 1 \end{cases}$$

(19)

Where: $C_d$ is the volume of the sphere.

Combine formula (18) and (19), we can get the following formula

$$\hat{f}_k(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K \left( \left\| \frac{x - x_i}{h} \right\| \right)$$

(20)

$$K_h(x) = \begin{cases} \frac{1}{2} C_d (d+2)(1-x) & x < 1 \\ 0 & x \geq 1 \end{cases}$$

(21)

Set $k(x)$ representing the contour function of $K(x)$, $g(x)$ is the negative derivative of $k(x)$, $g(x) = -k'(x)$, then the corresponding kernel function $G$ is $G(x) = C_g \left( \left\| x \right\|^2 \right)$, the probability density gradient estimation formula is

$$\hat{\nabla} f_k(x) = \frac{2}{nh^2 d^2} \sum_{i=1}^{n} (x - x_i) k \left( \left\| \frac{x - x_i}{h} \right\|^2 \right) = \frac{2}{nh^2 d^2} \sum_{i=1}^{n} g \left( \left\| \frac{x - x_i}{h} \right\|^2 \right) \left[ \sum_{i=1}^{n} x_i g \left( \left\| \frac{x - x_i}{h} \right\|^2 \right) - x \right]$$

(22)
Set \( \sum_{i=1}^{n} g_i \left( \left\| \frac{x-x_i}{h} \right\| \right) \neq 0 \), the mean shift vector is calculated as

\[
M_{k,G}(x) = \left[ \frac{\sum_{i=1}^{n} g_i \left( \left\| \frac{x-x_i}{h} \right\| \right)}{\sum_{i=1}^{n} g_i \left( \left\| \frac{x-x_i}{h} \right\| \right)} \right] - x
\]

The density formula for \( G \) at \( x \) point is calculated as

\[
\hat{f}_k(x) = \frac{1}{nh^2} \sum_{i=1}^{n} K \left( \frac{x-x_i}{h} \right)
\]

Then, the gradient calculation formula becomes

\[
\hat{f}_c(x) = \frac{C}{nh^2} \sum_{i=1}^{n} g_i \left( \frac{x-x_i}{h} \right)
\]

Finally, the Mean Shift vector for the center of the candidate area to move to the real target area is

\[
M_{k,G}(x) = \frac{h^2 \hat{\nabla} f_k(x)}{2\hat{f}_c(x)}
\]

By solving the maximum similarity between the target model and the candidate model, the target is continuously iterated from the initial position to the most likely target position to realize the feature marking.

3. MOTION FEATURE MARKING ALGORITHM

3.1. The Working Principle of the Algorithm

The working principle of the algorithm is to firstly consider the factors as results of the feature marking, the individual features of the sports students etc., and select the wireless sensor network node to collect the learning information of the sports students, then by used of mixed learning algorithm to do modeling for the features of the target athletic students. Finally, use the mean shift algorithm to do feature marking on the target, as shown in Figure 1.

3.2. Detection of Motion Targets

When the motion targets are in motion course, adopt sensor node to collect the information of sports students with each node using a mixed learning algorithm to establish the feature model. Comprehensively considering the sensor node limitations and reducing the calculated quantity, each pixel is only established 3 feature models, which are initialized according to the first image number. When the model weight is larger than the previously set feature threshold, it is regarded as feature model, otherwise target. When the target is detected, do pretreatment such as shadow removal, noise removal, cavity filling etc. on the detection results.

3.3. Construction of Performance Function

The design process of the motion feature marking algorithm based on the line sensor network shall not only consider the precision of the motion feature marking, but also the energy consumption of the sensor node, and according to the performance function determine the optimal sensor node and realize motion feature marking. The performance function includes two parts: (1) the effect of motion feature marking, adopting feature marking precision for measurement; (2) the residual energy of the sensor node, for the \( j \) targets, the sensor node energy consumption is
\[ \phi_{\text{corr}}(i) = \frac{(d_{c,i})^2}{H(s_i)} = -\sum_j p(E_{res}(i)) \log p(E_{res}(i)) \]  

Among them,

\[ (E_{res}(i)) = E_t - E_s(i) - E_n(i) - E_{rx}(i) \]  

Where: \( E_t \) is the node total energy consumption, \( E_s(i) \) is the perception energy consumption, \( E_n(i) \) is the energy consumption of the sent data, \( E_{rx}(i) \) is the energy consumption of the received data, \( d_{c,i} \) is the transmission distance.

The performance function is defined as follows

\[ f(i) = \arg \max_{\text{idx}} [a \phi_{\text{precision},j}(i) - (1 - a) \phi_{\text{corr}}(i)] \]  

Where: \( \phi_{\text{precision},j}(i) \) represents the precision of motion feature marking.

### 3.4. The Steps of the Feature Marking Algorithm

Step 1: Estimate the residual energy of the wireless sensor node and select the sensor node with more residual energy as the candidate node.

Step 2: Activate the candidate sensor node and collect the target information.

Step 3: Use the mixed learning algorithm to set up the feature model for each sensor node, realize the target detection, and extract the feature marking.

Step 4: Calculate the performance function of each candidate sensor node.

Step 5: Compare the size of the performance function value of the candidate sensor node, select the sensor node with the largest effect value to do motion feature marking, and make other candidate nodes in the sleep state.

Step 6: When the track of the target sports student goes beyond the perception range of the sensor node, reselect the optimal sensor node from other candidate nodes to realize feature marking.

### 4. SIMULATION TEST

#### 4.1. Experimental Environment

In order to verify the motion target effect of the algorithm in this paper, on the PC of Intel(R) Core(TM) 2Duo CPUE7500 @2.93GHz,8GBRAM, Win10OS, adopting VC6.0++ programming to realize the simulation experiment, and the experimental object is target of standard dataset (http://vision.stanford.edu/?birch/headtracker/seq/), Select the motion feature marking algorithm of the literature [10] for contrast experiments.

#### 4.2. Results and Analysis

##### 4.2.1. The Feature Marking Effect of General Sports Student Target

For the general sports, student target does feature marking test, the results below conclusions can be obtained:

1. The precision of the sports student feature marking of contrast algorithm is low and the deviation from the target center position is large, because the contrast algorithm has its own insurmountable defects, and it is difficult to obtain satisfactory results of sports student feature marking.

2. The precision of the sports student feature marking of the algorithm in this paper is higher than that of the literature [10], which is based on the first consideration of the factors such as feature marking results, node energy consumption etc. It selects the optimal wireless sensor network node to collect the target information, adopts the mean drift algorithm to do feature marking of the target, which reduces the adverse effect of the feature on the sports student feature marking, and obtains the satisfactory results of the sports student feature marking.

##### 4.2.2. Robustness Test

In order to analyze the robustness of the sports student feature marking, we select sports student target with gesture changes, different sheltering degree and analogs interference for test experiment. It can be clearly seen that the algorithm in this paper can do correct feature marking on the sheltered targets, and the robustness is better than the contrast algorithm.

##### 4.2.3. Probabilistic Neural Network and Hierarchical Regression Method Modeling

Probabilistic neural network (PNN) is a feedforward neural network developed by radial basis neurons and competing neurons jointly organizing. The theoretical basis is the Bayesian minimum risk criterion. The
working principle is as follows: input layer completes input sample preprocessing process (that is, the process of obtaining the input vector \( P \)), achieve the input sample space into a data space; the model layer calculates the distance between the input vector \( P \) and the weight vector \( IW \) to obtain a set of vectors which represent the similarity degree between the vector \( P \) and the vector \( IW \); The superposition layer firstly calculates the output sum \( n1 \) of the input vector \( P \) corresponding to the weight vector \( IW \), and then obtains the output vector \( a1 \) by the radial basis function non-linear mapping effect; the competitive output layer firstly obtains the weighted sum vector \( n2 \) of the vector \( a1 \), and then obtains the network final output value \( y \) according to the maximum value response in the vector mine.

The hierarchical data is usually expressed in terms of a sequence table, that is, with two variables associated with the orderly classified frequency table. The hypothesis test of this hierarchical data is to test whether there is a link between the two variables. So, we can quantify the two variables according to a certain scoring method, and then use the regression technology to analyze the dependency relationship between the two variables. Combining with the variance analysis, it decomposes the total variation into two parts as regression variance and the remaining does significance test on the regression coefficient to judge the degree of connection between the two variables.

In practical application of sports student feature marking, there are many conditions of online feature marking, so analyze the real-time of sports student feature marking algorithm, adopt target average feature marking time to measure the feature marking efficiency, with the results as shown in Figure 2. Do contrast analysis on the target average feature marking the time of each algorithm in the Figure 4, and find that the average feature marking time of the algorithm in this paper is less than that of contrast algorithm, and the quickening of speed of motion feature marking could satisfy the actual practical requirements of motion feature marking.

![Figure 2. Comparison of the average feature marking time for different algorithms](image)

5. CONCLUSIONS

The feature marking is a hotspot in computer vision research, and makes full use of wireless sensor nodes to collect real-time data on athletic students, and proposes a motion learning mixed model facing feature marking method. Firstly, it collects the information of the students, and uses the mixed learning model to do specific learning of the sports students, then adopts the mean shift algorithm to do feature marking on each sports student. It can be seen from the simulation experiment that the algorithm can improve the real-time of the feature marking through the cooperation between the wireless sensor nodes, adopt the learning mixed model to well solve the sheltering problem, improve the precision of the sports student feature marking, and speed up the speed of motion feature marking, thus the performance is better than current other motion feature marking algorithms.

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