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Behavior Prediction Based on Vision Judgment of Ball Carrier in Basketball Matches

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Abstract

The introduction of digital video technology into basketball trainings can greatly increase the efficiency of training; this thesis proposes a behavior prediction method based on the vision judgment of ball carrier to the computer technology used for the behavior prediction of ball carrier. The method analyzes the characteristics in basketball matches like complexity background, fast speed, and low resolution and so on, which integrate the multiple effective head vision characteristics, form the Riemannian manifold, and then map them into tangent space. Well-trained classifier is used to recognize the head pose of the ball carrier to ensure the visual range. This thesis makes prediction experiments for shooting, passing and dribbling of the ball carrier, and the simulation experiments shows that the proposed method is correct and efficient.

Keywords: *Vision Judgment, Riemannian Manifold, Basketball Match Videos, Particle Filter*

1. Introduction

The sports professionals abroad and at home made long terms of practices and researches, the results showed that bring in digital video technology into exercise training can greatly increase the training efficiency. Using computer picture processing, video analyzing and so on to analyze the video picture of training and matches, then getting useful information for the athletes and coaches to help the training, this has already became a hot-spot [1-2]. Now the application of computer technology for sports videos mainly reflected in the recognizing and analyzing of the athlete's behavior. Ramasso E and his colleagues used TBM(transferable belief model) to recognize flop, pole vault, triple jump and so on [3]; Roh M C and his colleagues tracked the key points of ballet dancers' body and got its dance course and realized auto analysis of the dance movements [4-7]; Tong X F and his colleagues realized the recognition of four swimming strokes of swimming match video [8-10]; Zhu G Y and his colleagues integrated considered the multiple information of the court in videos and realized auto analysis match tactics [11-14].

Basketball match is a wildly receipted and representative team sports, the win or lose relying on the close coordination among partners, and the good or bad of the coordination relying on the decision of the ball carrier. Therefore, the analyzing and predicting of the

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ball carrier's shooting, passing and dribbling has important guiding significance [15-17]. The behavior of ball carrier in a match belongs to complexity behavior analysis, located at higher level in movement analysis. It needs not only recognizes the behavior of ball carrier, but also the relationship with other partners and opposite basket, *etc.* present researches in our country mainly focusing on the behavior recognition of human body, there're few prediction researches [18]. Duque D and his colleagues proposed an abnormal behavior prediction method based on N-ARY TREES classifier, later proposed a dynamic oriented graph (DOG) which is more real-time and self-adapt, and used it to predict abnormal behavior [19]. But in real life, the prediction of human body is more efficient than the recognition, as in bank, airport, government building and those places which is sensitive in security, if the intelligent monitoring system can predict the criminal behavior of suspicious individuals in advance and alarm the security guard, the criminal can be prevented efficiently, and can reduce the costs in personnel and finance; in sports matches, if the ball carrier's behavior is recognized ahead, the match's situation can be predicted.

In the video of basketball game the images are not clear because basketball players move fast, and then how to effectively predict the behavior of the players through various forms of players? In this paper, through the detection and classification of players and the head recognition to the ball carrier, the distribution of both players on the field and the vision information of the ball carrier can be obtained. The prediction algorithm is used to predict the ball carrier's behavior in artificial potential field. When the ball carrier is in the process of selecting the behavior he will choose different behaviors according to the amount of information and the distance between themselves and their teammates. As a ball carrier, he can choose to shoot, pass and dribble. While for these three behaviors, shooting has the highest priority, followed by passing, dribbling, that is, if the possibility of successfully shooting is high, the ball carrier will chose to shoot; otherwise the ball carrier will chose to pass the ball to teammate with a better position; if the teammate with a better position is found, then the ball carrier will select pass, otherwise select dribble.

This text proposed a new prediction technology used for the ball carrier's behavior in basketball match videos. Analyzed the characteristics in basketball matches like complexity background, fast speed, low resolution of head and so on, integrated multiple effective head vision characteristics used covariance and formed Riemannian manifold, then mapped them into tangent space, used well-trained classifier *LogitBoost* to recognize the head pose of the ball carrier and ensured the visual range. According to the players' distribution in the visual range, used player's information based on artificial potential field, predicted the shooting, passing and dribbling of the ball carrier.

2. Vision Judgment of Ball Carrier

Before recognizing the head pose of the ball carrier, uses the method which combines manually labeling and particle filter tracking, ensures the positions of each players in the graph. In order to judge all the player's visual range, it needs to further ensure the head pose of the ball carrier, that is, judges the angle which the head is about to turn as one of the eight angles in graph 1. Nowadays head pose recognition algorithm mainly aims at the situation which the human-computer interaction has good graph, higher resolution, the head characteristics can be efficiently extracted, while basketball matches exists many noise, motion blur, small proportion of head in the graph, low resolution, the characteristics which can be extracted are limited.

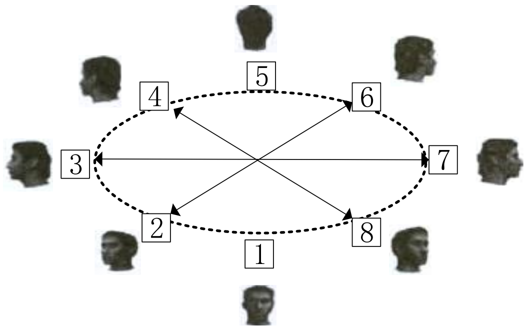

Figure 1. Eight Head Poses

Tuzel O and his colleagues proposed a human detection algorism with strong robustness to the changing external environment, he regarded inputted graph which making human detection as a dichotomy problem with foreground (human body) and background, and made experiments on datasets INRIA and Daimler Chrytel, which got pretty detection effect. On this basis, this text explored human detection dichotomy problem as multi-classification problem, finished head detection and head poses recognition at the same time, as the same application condition and they are both detection classify problems.

A. Head Features Extraction Based on Riemannian Manifold

For each training sample, firstly extracts N equal-area squares in this graph, this N small areas allows partial overlapping. For each pixel in each extracted area, calculates a 12 dimension feature vector

$$\lambda = \left[y\, xhg\, r_x\, p_x\, oGxy \left\{ 0, \pi/2, \pi/4, \pi/6 \right\} \right]$$

In this formula, x and y is the coordinate of pixel, R, G, and B is three color channel value, r_x and p_x is the first derivative, O is gradient direction, Gxy {0,π/2,π /4,π /6} respectively uses the response value of Gabor filter with 2×4, 16 as sinusoidal frequency, 0 as direction, π/3, π/6, 4π/3. The reason for extracts color features is that the head skin color and other not skin color counts different proportion in different angles (like front and back), while Gabor filter is for extracting textural features of the head. Then calculates the each area's corresponding covariance descriptor

$$p_{ri}\left[x_k^i \right] = 1/9 \tag{1}$$

In this formula, λ_x^p refers to the mean vector of all the pixel's feature vector in k sample's r area, y_x^p refers to the number of pixel in k sample's r area. t_i Refers to the feature vector in this area's I pixel. λ_x^p is a symmetric matrix, the components in leading diagonal are the variance of each feature, other non-diagonal components are the relevant coefficient in each feature. Tuzel O also proposed a method using integral image to calculate covariance descriptor in a fast speed, each rectangle's corresponding covariance descriptor can be calculated in the time complexity as O (d2), d is the dimension of each pixel's feature vector.

As covariance descriptor cannot form vector space so as cannot to use classical method used machine learning to form the classifier. But in mathematics, is has the structure attributes of symmetric and positive semi-definite. Fletcher P T and some others pointed that, $n \times n$ symmetric positive semi-definite matrix set formed a convex cone of n ($n+1$) /2 dimension space. As their variance is impossible to be 0 when calculating each graph's feature, it just needs to consider the condition then covariance matrix is nonsingular (symmetric and positive definite). While symmetric positive definite matrix's set is corresponding to the inner part of convex cone of the symmetric positive semi-definite matrix, this inner part is a differential manifold, so the differential geometry method can be used to make subsequent processing. Pennec X and his colleagues proposed the affine Invariant measurement in differential manifold. It's a continuous Riemannian metric with main thought: arbitrarily point gets though Riemannian manifold M, all can be as a tangent space SX, and forms diffeomorphism for tangent space SX and Riemannian manifold M. Tangent space is a linear space formed by all the tangent vector of some point. For the vector V in tangent space SX, can map V into the isometric and synclastic geodesic started from point X in Riemannian manifold M by exponential map $\exp_x(x)$. The definition of exponential map $\exp_x(x)$ is:

$$p = \exp_x(x) = y\frac{1}{2}\exp\left(p^{\frac{1}{2}}\exp\left(y^{-\frac{1}{2}}xp^{-\frac{1}{2}}\right)\right)y^{\frac{1}{2}} \tag{2}$$

And the inverse mapping of exponential map, that is, log mapping $\log_y(x)$, mapping the geodesic from point X to Y in Riemannian manifold M as the isometric and synclastic vector in tangent space s_x.

$$p = \log_y(x) = y^{\frac{1}{2}}\log\left(y^{-\frac{1}{2}}xy^{-\frac{1}{2}}\right)x^{\frac{1}{2}} \tag{3}$$

This exponential map and log mapping forms the double continuous mapping between tangent space SX with Riemannian manifold M. Through this double continuous mapping, the points in Riemannian manifold M can be transferred into tangent space SX and makes researches. So this affine invariant measurement method can be used into the differential manifold formed by covariance descriptor of graph feature and makes it Riemannian manifold, then turns to tangent space, uses machine learning method in linear space to detect and recognize the player's head poses.

But when goes through arbitrary point X in Riemannian manifold M, it can be a tangent space SX, so there are countless tangent spaces, it must be a unified tangent space as the mapping space of arbitrary point X. For a bunch of points $(y, y_1, y_2 ..., y_n - 1, y_n)$ in Euclidean space, usually takes the mean value as it optimum value to operate. For a bunch of points $(x_1, x_2, ..., x_n - 1, x_n)$ in Riemannian manifold M, as the same rules, the mean value of these points forms a tangent space and gets best approximation of the manifold. Document [16] proposed a Karcher mean value of differential manifold

$$\lambda = \arg\min_{\eta \in N} \sum_{k=1}^{M} r^2(x_i, y) \tag{4}$$

The formula requires the smallest mean value and smallest sum of the squared distance among each point Xi in Riemannian manifold M. There the squared distance is

$$r^2(x, y) = tr\left(\log^2\left(x^{-\frac{1}{2}}xy^{-\frac{1}{2}}\right)\right) \tag{5}$$

As for the convex cone manifold formed by covariance descriptor, the mean value of Karcher is unique, can takes gradient descent

$$\gamma^{t+1} = \exp_{\gamma^t}\left[\frac{1}{M}\sum_{i=k}^{m}\log_i(y_i)\right] \tag{6}$$

Values mean value γ, when

$$t\left(\gamma^{r},\gamma^{r+1}\right)\prec\varepsilon \tag{7}$$

Circulation stops. Makes tangent space $s_{\gamma at}$ point γ, then gets the most reasonable approximation. Finally orthogonalized the mapped vector as formula (8)

$$\gamma ec_{\gamma}\left(x\right)=\gamma ec_{i}\left(\gamma^{-\frac{1}{2}}x\gamma^{-\frac{1}{2}}\right) \tag{8}$$

In this formula, makes $\left(\gamma^{-\frac{1}{2}}x\gamma^{-\frac{1}{2}}\right)=p$, and gets

$$\gamma ec_{i}(p)=\left[p_{1},1,\sqrt{2p_{1,2}},...,p_{2,2},\sqrt{2}p_{2,3},...,p_{n,n}\right] \tag{9}$$

B. The Training of Detection Classifier

Through above-mentioned calculation, all the sample's covariance descriptor x_k^r of r areas can be turned into the orthogonalized feature vector in tangent space of mean points and forms feature set A_r = { x_k^r | 1 ≤k ≤M}, 1≤r<N}, x_k^r refers to the extracted feature vector after the k sample r area transferred. Then takes A_r as training set, trains a multiclass *LogitBoost* detection classifier for each small area, the final detection result is voted by all the small area's *LogitBoost* , explored multiclass *LogitBoost* training algorithm is as following:

Inputs: the head graph training set and non-head graph set (x_1^k, y_1), …, (x_k^r, y_n) in different external conditions and different angles, there x_k^r is the I sample's k part's corresponding integrates multiple head poses' covariance descriptor, y_i ∈ { 1,2,3,4,5,6,7,8,9} , respectively refers to eight different head poses and non-head graph's class label in Figure 1.

a) Calculates all the inputted head samples' tangent space Karcher mean value γ_k of covariance descriptor in k area by gradient descent and maps it into mean value's tangent space by log mapping $\log_{\gamma^k}(x_k^r)$, then in the form of orthogonalization, that is

$$x_k^r=vec_{\gamma^k}\left(lpog_{\gamma^k}\left(x_i^k\right)\right)$$

b) Initializes weight value $x_k^r=1/N, i=1,...,n,\ f_j\left(x_k^r\right)=0$, $p_{ri}[x_k^r]=1/9$.

c) Loop iterating and gets weak classifier supposes

$$for 1=1,2,...,L\ do$$

$$for\ j=1,2,...,9do$$

(1) Calculates returned target value and weight value

$$x_k^r=pr_i\left[x_i^y\right]\left(1-pr_j\left[x_i^y\right]\right)$$
$$t_{ij}^x=\frac{y_{ik}^{k_i}-pr_i\left[x_i^j\right]}{pr_j\left[x_i^j\right]\left(1-pr_j\left[x_i^k\right]\right)} \tag{10}$$

(2)Fits weak classifier function by weighted least square method

(3)Updates $x_j\left(x_k^r\right)$

$$x_j\left(x_k^r\right)\leftarrow x_j\left(x_k^r\right)+x_{ij}\left(x_k^r\right) \tag{11}$$

There,

$$x_{ij}\left(x_k^r\right)=\frac{6}{8}\left(y_{ij}\left(x_k^r\right)\right)-\frac{1}{8}\sum_{t=1}^{7}x_{ik}\left(x_k^r\right) \tag{12}$$

(4)Updates $pr_j\left(x_k^r\right)=\dfrac{e^{x_j\left(x_k^r\right)}}{\sum_{i=1}^{8}e^{x_k\left(x_k^r\right)}}$

(5) Save

$$x_j=\left\{g_{il},\gamma^k\right\} \tag{13}$$

End for

End for

4) Save { $x_1,...,x_{10}$ }.

There parameter L is the iteration number of *LogitBoost* , $L=\max_j\{accuracy_1(j)\geq \tau_{accuracy}\vee\ (accuracy_1(j)-accuracy_{j-1}(j))\leq\tau_{background},\ \forall j\in\{1,...,8\}\}$ Accuracy l(j) refers to j classifier's accuracy after I times of iteration, $accuracy_1(j)-accuracy_{j-1}(j)$ is the learning rate, which refers to the increasing level of the classifier's accuracy after two continuously iterates.

C. Classification and Detection

As it supposes that the ball carrier's detection is finished and labeled by rectangular box, thus makes detection and recognition of its head, it only needs to sweep 1/4 of the body's rectangular box by detection window, the steps are as following.

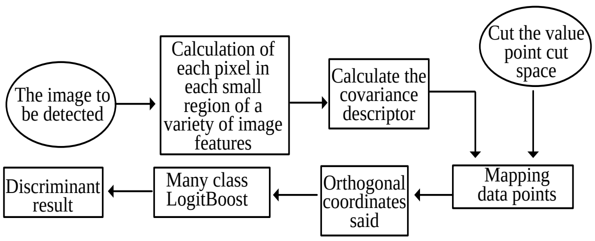

Figure 2. Flow Chart of Head Poses Recognition

When detection window moves, respectively calculates each area's covariance descriptor at this window, then takes Karcher mean value point μ_k maps into tangent space by log mapping and orthogonal it. Makes the gotten feature vector as the trained multiclass *LogitBoost's* input, finally takes all the small areas recognition result, counts and judges the head poses by formula (14).

$$Label=\arg\max_k\left\{t_c\right\},k=1,...,h \tag{14}$$

In this formula,

$$t_k=\sum_{k=1}^{m}\left(LB_i=i\right) \tag{15}$$

Refers to the judgment result is the sum of k class of small area, LB_i is the judgment class given by I area's *LogitBoost* classifier.

The complexity of head recognition algorithm mainly focus on the calculation of head features, while the complexity of calculating covariance descriptor is O (d2), maps covariance descriptor into tangent space and makes logarithm transformation and the time complexity is O (d3), d is the extracted feature's dimension.

3. Behavior Prediction

Through the player detection classification and the head poses recognition of ball carrier, the both side's distribution and the ball carrier's visual information can be learned. Proposes the ball carrier's behavior prediction algorithm based on artificial potential field.

The ball carrier can choose different behavior according to himself of the partner's information and distance in their behavior choosing process. As a ball carrier, we can chooses shooting, passing or dribbling. In this three behavior, shooting ranks the first place, then passing and dribbling, that is, the biggest success possibility for ball carrier is shooting, then chooses shooting; or to find the partners whose position are better, if found, chooses passing, or chooses dribbling.

A. Player's Information Amount Based on Artificial Potential Field (APF)

In a match, the offensive side's player can be divided into two parts, the ball carrier and the member without the ball. The offensive player's information amount can be referred and calculated by artificial potential field (APF). The artificial potential field of player x can be expressed by

$$U_{apx}(y) = U_{goal}(y) + U_{obs}(y) \tag{16}$$

In this formula, $U_{apx}(y)$, $U_{goal}(y)$ and $U_{obs}(y)$ respectively refers to artificial potential field, attractive potential by goal and rejection potential by barrier. The attractive potential can be expressed by

$$U_{goal}(y) = \frac{1}{2}kp\left(\frac{1}{y - y_{goal}}\right)^2 \tag{17}$$

In this formula, $y - y_{goal}$ refers to the distance between the offensive player and opposite basket, the smaller it is, the attractive potential is bigger; the bigger it is, the more far distance is, the attractive potential is smaller. The rejection potential can be expressed by

$$U_{obs}(y) = \begin{Bmatrix} \frac{1}{2}kh\left(\frac{1}{r} - \frac{1}{r_0}\right)^2 r \le r_0 \\ 0 \quad r \succ r_0 \end{Bmatrix} \tag{18}$$

Barrier refers to opposite players, ρ in this formula is the distance between the offensive player and the surrounding opposite player. r_0 Is a distance threshold, once exceeds r_0, the player will not be rejected by the opposite players, that is, opposite players will not threaten this player. If there are multi opposite players in the offensive player's efficient range (r≤r_0), it needs to consider multi players' rejection potential $U_{obs}(y)$ when calculating this offensive player's artificial potential field.

As the player's character(forward, guard and so on) cannot be directly judged in the match video's graph feature, the algorithm of auto updating parameter k_p (shooting ability) and k_d (tackling ability) by the number of player tackling and shooting is proposed. Firstly establishes a shooting and tackling ability chart of the 10 players in the court, as Table1.

Table 1. Shooting and Tackling Ability Chart (Initial State)

	Player number									
	X_1	X_2	X_3	X_4	X_5	y_1	y_2	y_3	y_4	y_5
k_p	α	α	α	α	α	α	α	α	α	α
k_d	β	β	β	β	β	β	β	β	β	β

B. Ball Carrier's Behavior Prediction

Each time, calculates the information amount $\gamma x = UAPF(x)$ for each player x, the ball carrier chooses different behavior according to the information of himself and his partners. The ball carrier's behavior prediction can be abstracted as path choice problem as Figure 3(blue and white rectangular boxes refers to both side's distribution, five-pointed star refers to the opposite basket).

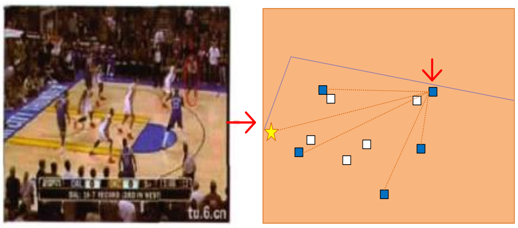

Figure 3. Example for Ball Carrier's Behavior Choosing

When the ball carrier's information amount $\gamma_c \succ \gamma_0$ (γ_0 is the shooting information amount threshold), refers to it's close to the opposite's basket and the threaten made by opposite player is small, the successful shooting possibility is bigger, then chooses shooting; when the ball carrier's information amount $\gamma_c \succ \gamma_0$, the successful shooting possibility is smaller, then chooses passing or dribbling.

Whenτc≤τ0, the choice of passing or dribbling must be decided by the proper partners. Then finding partners, the better shooting condition (attractive potential $U_{goal}(y)$ is bigger, rejection potential $U_{obs}(y)$ is smaller) and the distance between ball carrier and the partners should be both considered. The far distance is, the passing is more likely to miss or be broken; the closer, the successful rate is bigger. Therefore, the k partners surrounding ball carrier's visual range, calculates the successful passing proportion from player c to his partner m by this following formula

$$y^x_m = \frac{[r_m]^\varphi [\varphi_m]^\varphi}{\sum_{m \in parter} [\gamma_m]^\varphi [\varphi_m]^\varphi}, m \in partner \tag{19}$$

In this formula, $partner_c$ refers to the set of visual range of ball carrier c and links to k partners with no defensive players. y_m *calculates* as following

$$y_m = \frac{1}{t_{xm}} \tag{20}$$

In this formula, t_{xm} refers to the distance between ball carrier c and partner m. the distance ($y - y_{goal}$) of formula (18), (19) and (20)

According to formula (19), the possibility value of passing to partners in the visual range can be calculated, then finds out the best partner i, that is

$$t_i^k = \max\{t_m^f \mid m \in partner_c\}\ i \in partner_c \tag{21}$$

Then judgment by conditions:

1) If $partner_c$ is not empty and $t_i^k \geq r_0$, there r_0 is a adjusTablepossibility threshold, then ball carrier chooses to pass to partner i.

2) If $t_i^k \geq r_0$ or $partner_c$ is empty, the ball carrier c cannot find a proper partner, the ball carrier c chooses dribbling. The behavior prediction is mainly judged by formula (9)-(13). Analyzes the artificial potential field UAPF of each player as initial operation, the complexity of the formula depends on the number of visual partners. So this algorithm's complexity expresses as linear staircase, showed as O (n), n is the number of visual partners.

4. Experiments and Analysis

In order to prove the efficiency of ball carrier's behavior prediction algorithm, makes hybrid programming in the computer with 2.8 GHz of CPU dominant frequency, 3 GB RAM, uses C + + and MATLAB. Firstly tests the recognition algorithm for the ball carrier's head poses, on this basis, further proves the efficiency of ball carrier's behavior prediction algorithm.

A. Head Poses' recognition Experiment

In order to train the multiclass *LogitBoost* classifier introduced in chapter 2.2, manually intercepts 800 head graphs from 100 basketball match videos, each class 100 graphs. The size is between 10×10 and 30 ×30, including the outlook of different people, like bald, beard, complexion and the change of light. After intercepting, unifies into the size of 20×20 (as the covariance descriptor has "scale invariance", it's unnecessary to unify the testing graphs, unifies the graphs is only for the same size of training set graphs), as the sample of training multiclass *LogitBoost* classifier, the classical training sample is as Figure 4. Besides, intercepts 100 non-head graphs as counter-example training set, mainly including part of the court background graphs and other parts of the player's body. Figure 5 shows the relationship between the square area's relative size (the ratio to sample length) extracted from training samples and the recognize accuracy. It shows the highest accuracy when it length to sample length ratio is 0.28. When training processes, sets τ accuracy of head graph detection classifier as 0.99, learning rate as 0.1, τ accuracy of non-head graph detection classifier as 0.4. Extracts other 400 head graphs as training set, each class 50 graphs, the experiment result is as Table2.

From chart 2, the error judgment mainly appears in the judgment of the neighbored two head poses. It's mainly because the low resolution of head graphs in basketball match videos, the noise disturbing and the similarity of the head poses. The experiment result shows, the covariance descriptor integrated multiple bottom-layer can better adapt those situations, the method in this text got a desirable experiment result, the average recognition rate of eight head poses reaches 97.4%.

Figure 4. Classical Training Samples of Classed Head Poses

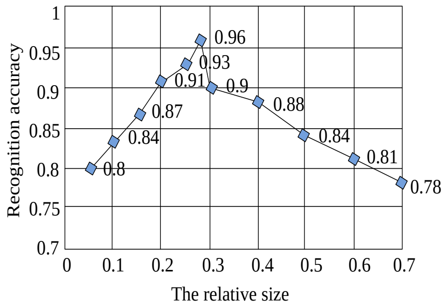

Figure 5. The Relation Curve between Head Poses Recognition Rate's Accuracy and Small Area's Relative Size

Table 2. The Experiment Result of Head Poses' Recognition

readings	0	46	91	137	190	229	278	321
0	0.9	0.01	0	0	0	0	0	0.02
46	0.02	0.97	0	0	0	0	0	0.02
91	0	0.02	0.96	0	0	0	0	0.02
137	0	0.01	0	0.9	0.01	0	0	0.02
190	0	0	0	0	0.99	0	0	0.02
229	0	0	0	0	0.01	0.97	0	0
278	0	0	0.02	0	0.01	0	0.9	0
321	0.03	0.01	0	0	0	0.01	0	0.96

B. Behavior Prediction of Ball Carrier

Extracts 10 basketball match videos whose frame rate is 25 frame/s, the integral levels of two sides are closed. The shot cut in basketball videos are manually divided into individual shots, respectively analyzes each shot. Each shot corresponding to a kind of movement (shooting, passing, dribbling), the experiment data shows as Table3. In the experiment, takes 2/3 of each kind of sum shot as training video, uses to estimate each parameter in behavior prediction algorithm, 1/3 of the sum as testing videos.

Table 3. Data Description of Behavior Prediction Experiment

showings number	shooting lens number	ball lens number	Dribble shot number
1	42	48	29
2	43	53	32
3	46	47	34
4	37	49	37
5	38	50	32
6	39	44	40
7	42	59	42
8	55	63	36
9	51	64	30
10	48	59	38

When valued bigger of shooting information amount τ0, it might be mistaken predict shooting as passing, when valued smaller, it might be mistaken predict passing as shooting and made the shooting prediction accuracy reduced. The same as for dribbling information amount r_0, when valued bigger, it might be mistaken predict passing as dribbling, when valued smaller, it might be mistaken predict dribbling as passing and made the prediction accuracy reduced. According to big amount of experiments, respectively took the mean value of shooting player APF's information amount and the dribbling player APF's information amount in training video as the value ofτ0 and r_0, the prediction accuracy is the highest. For distance threshold r_0, counts each time the distance from the success tackling player to the ball carrier, extracts the highest value as distance threshold r_0. The sets initial value of shooting ability k_p and tackling k_d as 1. In order to ensure the parameter and φ in formula (19), sets ratio = 0/φ, according to the comparison of ratio with prediction accuracy rate under different ratio to ensure parameter and φ. The experiment result is as Figure 6, the prediction accuracy rate is

$$R_p = \frac{\sum_{i=1}^{13}\left(\gamma^i_{shooting} + \gamma^i_{pas\sin g} + \gamma^i_{dribbling}\right)/2}{13} \tag{22}$$

In this formula, $\gamma^i_{shooting}$, $\gamma^i_{pas\sin g}$ and $\gamma^i_{dribbling}$ respectively refers to the accuracy rate of predicting shooting, passing and dribbling in i match. The experiment, individually sets θ and ϑ as 2 and 1. The upper limit value θ_d and shooting ability θa of tackling ability are set as 5 and 25. The statistics is as chart 4 of 10 experiment.

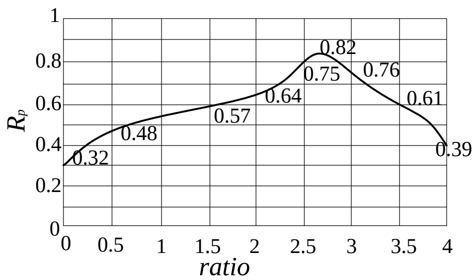

Figure 6. The Relation Curve between Prediction Accuracy and Ratio

From Table4, the average prediction accuracy rate of shooting and dribbling is high as above 80%, while the accuracy of passing is low. It's mainly because when calculating passing accuracy, not only needs to consider the algorithm can predict as passing but also values the catching partner .the analyzing result shows, the reason for error judgment is: 1) In basketball matches, the behaviors of ball carrier are affected by some specific non-accidental factors and some accidental factors (as physical strength, injury), and with randomness; 2) Being restricted by some tactics and the cooperation of partners. These all causes the error judgments.

Table 4. Experiment Result of Behavior Prediction

showings number	The prediction of movement		
	shoot	Pass ball	dribble ball
1	89	75	84
2	83	74	78
3	86	72	84
4	82	83	76
5	92	80	73
6	83	73	85
7	86	73	80

8	84	74	83
9	85	74	82
10	91	82	85
average correct rate	85.9	76.1	81.3

5. Conclusion

Sports video has becoming a highlight of present computer vision field, while present researches are mainly focusing on the detection and tacking, analyzing the extracted movements, which belongs to bottom-layered video analysis technologies. This text proposed a new technology which predicting the ball carrier's behavior in basketball matches. Aiming at the complex background, fast speed of players, low resolution and so on, integrated multiple effective head vision characteristics and formed Riemannian manifold, then mapped them into tangent space, used well-trained multiclass *LogitBoost* to recognize the head pose of the ball carrier and ensured the visual range. According to the players' distribution in the visual range, used player's information based on artificial potential field, predicted the shooting, passing and dribbling of the ball carrier. This two experiments showed the method is validity and efficient. The behavior choice in basketball matched is a pretty complexity decision process under the effect of many other elements, to find out more efficiently information and increase the prediction accuracy are worthy to be further researched.

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