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A empirical research on AI-powered athletic posture detection in sports training

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Abstract

The current investigation delineates the efficacy of AI-facilitated detection of athletic postures within the realm of sports training. Employing a synthesis of literature review and empirical methodologies, data were amassed and scrutinized, affirming the study's validity. The salient outcomes are manifold: (1) The frame difference algorithm efficaciously discerns inter-frame variances, evidencing pronounced adaptability and robustness, thereby enabling the recognition of weightlifting postures. (2) Confronting the challenge of negligible inter-frame disparities inherent in the frame difference algorithm, the research introduces a novel detection technique predicated on the cumulative inter-frame differences, which precisely pinpoints regions of posture alteration in weightlifting athletes. (3) Leveraging the dynamic space model of optical flow, the study ascertains the directional channel predicated on optical flow trajectory analyses, facilitating the identification of three distinct weightlifting postures: squatting, descending, and standing. (4) In alignment with the distinctive postural attributes of weightlifting athletes, a human posture paradigm was formulated, and a BP neural network classifier was deployed for both training and evaluative purposes, culminating in the successful differentiation of athlete from non-athlete entities within the training milieu. (5) The application of AI in posture recognition was extended to the scrutiny of pivotal postures and motions in weightlifting athletes, with experimental findings revealing a 98.21% accuracy rate in the recognition of force-exertion postures via the inter-frame difference method, and a flawless 100% accuracy in the identification of the apex and squatting postures. The enumeration of detected postures—encompassing knee extension, knee flexion, force application, squatting, and standing—through the poselet keyframe extraction approach, corresponded with the video count. Prospectively, AI's role in athletic posture detection promises to augment coaches' and athletes' comprehension of their proficiencies and deficiencies, thereby steering training refinement and bolstering both the efficacy of training and the athletes' caliber.

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1. Introduction

At the forefront of intelligent sports, the introduction of Artificial Intelligence (AI) into athletic posture analysis signals a transformative shift from traditional training methodologies, offering a robust tool for the precise delineation of athletes' stances. Specifically, under the auspices of China's ambitions to excel in both sports and AI, the integration of sports training with AI-centric detection technologies has intensified. This synergy has garnered significant scholarly interest, prompting extensive and meticulous investigations that provide theoretical foundations for the pragmatic application of AI in discerning athletic postures by coaches, thereby refining training regimens and enhancing training efficacy. In practical applications, AI's ubiquity extends across military fitness, educational sports programs, and professional athletic training, notably exemplified in the Olympics via 3D tracking technologies that reveal subtleties beyond human perception, facilitating intelligent adjudication through computer vision, and effectively serving as a digital coach. Theoretically, the development of an embedded AI detection and recognition system, coupled with the employment of BP neural network classifiers, establishes the framework for posture detection. This inquiry augments the theoretical corpus and offers substantial academic support. Practically, the integration of AI in identifying weightlifting postures during training is aligned with diverse training contexts, enabling coaches to rectify incorrect techniques through AI-assisted video analytics. This research also serves as a beacon for other sports mentors, advocating the adaptable application of AI in posture detection tailored to specific sporting disciplines and training objectives, thus ensuring training efficacy and contributing to the burgeoning prowess of China's sports domain.

The scholarly landscape of posture detection, both domestically and internationally, has been marked by significant advancements. Ren posited in his master's thesis that polyhedral robots are congruent with the exploratory demands of contemporary times, with robotic technology and a universal kinematic model for polyhedral robots facilitating posture detection in intricate environments [1]. Zhang elucidated in his master's thesis that the application of the deepskeleton network to extract skeletal data from weightlifters' videos is instrumental in pinpointing key postures, thereby aiding coaches in the training process [2]. Fan et al. discerned that deploying deep learning for interactive human-computer posture detection predominantly involves a dual-network architecture for service robots, which is pivotal in detecting the quintessential grasping posture, effectuating precise calculations, and pinpointing the optimal grasping locus, culminating in the consummation of posture grasping [3]. Hou and Zhou demonstrated that the utilization of the YOLOv4 network structure for individual

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posture detection in educational settings entails a sequence of image data procurement, dataset compilation, training, pre-trained model development, and framing operations, thereby ensuring an accurate comprehension of classroom postures [4]. Han discovered that the requisites for athletes' efficient training necessitate enhanced BP neural network algorithms, which are adept at accurately identifying human postures, thus contributing to the augmentation of sports skills [5].

Internationally, scholars have embarked on multidimensional human posture detection research predicated on various scenarios, initially employing deep learning to dissect issues related to human posture detection. Toshev and Szegedy expounded that the DeepPose model is proficient in predicting joint coordinates [6]. Tompson et al. revealed that the optimization of human posture joint points is achieved through the utilization of stacked two-dimensional Gaussian functions, engendering heatmaps, and thereby fulfilling joint point regression tasks [7]. Pfister et al. ascertained that the enhancement of heatmaps necessitates video image predictions of contiguous frames, which are facilitated by optical flow data, buttressed by the Flow Convent model [8]. Newell et al. highlighted that the amalgamation of network structures and the employment of convolutional residual networks to procure spatial features, in conjunction with the integration of multi-scale feature channels, significantly bolsters target detection efficiency [9]. With the advent of motion posture detection in the sports domain, research endeavors have progressively shifted towards AI-based posture detection in sports.

Regarding AI-based Posture Detection Research, Gu deduced in her master's thesis that the KNN algorithm's application to treadmill monitoring videos, encompassing object tracking and image processing, facilitates the recognition of human postures, rectifies running postures, and enhances the impact of running on physiological functions [10]. Ke indicated that the procurement of images of athletic postures via embedded devices proffers informational support for AI-driven athletic posture detection, which, in turn, provides feedback to athletes, enabling them to adjust their movements in accordance with AI posture detection outcomes, thereby achieving efficacious and qualitative exercise [11]. Post-2020, scholars such as Ma have concentrated on 3D human posture estimation and action recognition predicated on deep learning [12-14]. International scholars have pioneered AI posture detection research, establishing a comprehensive theoretical framework and yielding reliable research findings. Some American researchers have delved into AI-accelerated computing platforms, proffering novel insights for the evolution and application of AI-specific training apparatuses. Concurrently, others have investigated AI-based posture detection models, utilizing model data analytics to steer correct postural alignments.

Within the scholarly domain, domestic research on posture detection and its AI-enhanced counterpart commenced belatedly, characterized by a nascent theoretical framework and a paucity of depth and specificity in model architecture and algorithmic support. Conversely, international research on AI in sports posture detection has not adequately accounted for cross-regional and cross-cultural considerations. This investigation, cognizant of national imperatives, harnesses AI to discern athletic postures in sports training, building on antecedent studies to elucidate the theoretical underpinnings and delineate precise methodologies for integrating AI posture detection within sports training paradigms. The objective is to meticulously detect athletic postures via AI within the training context, rectify postures based on analytical outcomes, and thereby enhance training efficacy. Methodologically, the study amalgamates literature review and experimental techniques. The exposition is structured into four segments: an introduction, an exposition of the research methodology, a presentation of results and discussion, and a concluding synthesis. The research's impact is manifold, bolstering the empirical exploration of AI in athletic posture detection for sports training, establishing a bedrock for future inquiries; methodically pinpointing and rectifying movement inaccuracies through AI detection, steering the enactment of precise movements, and amplifying training productivity; and enriching the integration of sports training with AI posture detection, fostering intelligent training modalities, and propelling athletes' performance enhancement.

2. Research methods

2.1 Frame difference method

In addressing the computational exigencies local to AI-enhanced athletic posture detection for sports training, a system capable of offline detection and recognition has been instituted. This system is tailored to satisfy the environmental perception and interactive requisites of weightlifting training [12]. The integration of microprocessor technology within portable smart devices has been executed to curtail the expenses associated with AI detection, thereby catering to the demand for cost-effective, high-performance AI detection and the precise discernment of weightlifting athletes' maneuvers. Consequently, the establishment of an embedded AI detection and recognition system platform has been realized. The constructed architecture, delineated in Figure 1, encompasses three principal components: the procurement of imagery, the processing thereof, and the subsequent output of processed images.

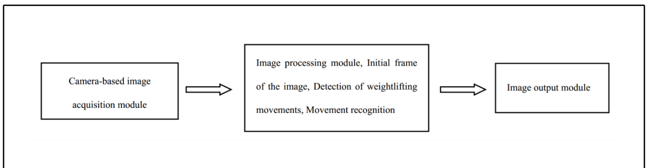

Figure 1. Architecture of the embedded AI-based detection and recognition system

The architecture depicted in the Figure 1 demonstrates the process of capturing video footage of weightlifting athletes during training sessions using a camera. The video images are then subject to initial frame processing, where the frame difference algorithm is employed. As the weightlifting athletes perform different movements in the video, changes occur in the grayscale values of adjacent frames. These changes are calculated by determining the absolute values of the differences. Following this, a threshold analysis is conducted to identify the movements and postures of the athletes, thereby achieving AI-powered athletic posture detection [13]. The equation for calculating the differential images $D(x,y)$ is:

$$\mathrm{D}(x,\ y) = \begin{cases} 1, & \text{if} \,|\, \mathrm{I}(t) - \mathrm{I}(t-1) > T \,| \\ & 0, \text{others} \end{cases} \tag{1}$$

where $I(t)$ represents the image at time t, $I(t-1)$ represents the image at time $t-1$, T is the threshold value for the binarization of the difference image. When the difference image is 1, it represents the foreground; when it is 0, it represents the background.

The application of the frame difference algorithm allows for the convenient acquisition of inter-frame differences. It is highly adaptable to the weightlifting training environment and, due to its robustness, can effectively recognize the postures of weightlifting movements.

2.2 Frame difference accumulation method

In the milieu of weightlifting training, the backdrop remains static, allowing for the athletes' maneuvers to transpire within a predefined vicinity. This staticity ensures that AI-driven posture detection is sharply attuned to the athletes' foreground activities [14]. Subsequent experimental inquiries proceed as delineated: Commencing with data sampling within the detection zone, followed by the implementation of optical flow tracking. Subsequently, the tracking outcomes inform the segmentation of channels and the execution of pertinent computations. Culminating in the discernment of pivotal posture frames within weightlifting sequences, these frames demarcate the training regimen into distinct stages. The methodology underpinning the detection and analysis of athletic postures throughout the experimental phase is encapsulated in Figure 2.

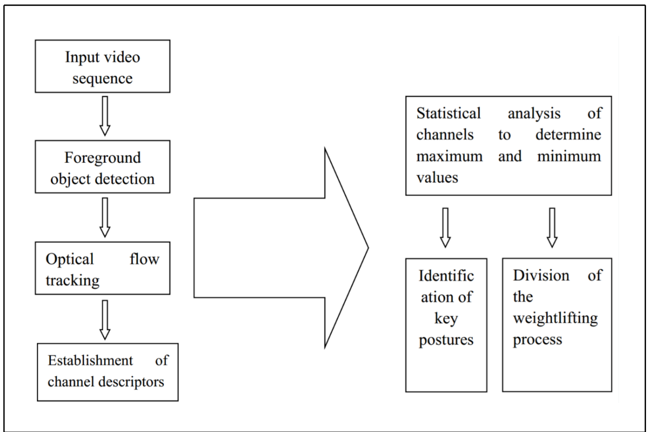

Figure 2. Map of athletic postures detection in experimental phase

Utilizing the frame difference methodology, an investigation was conducted to ascertain the foreground region within weightlifting video footage. The detection of this area was impeded by extraneous variables, necessitating the grayscale imagery to undergo binarization, erosion, and dilation processes to enhance the delineation of weightlifting postures [15]. It was observed that the gradual squatting motions of the athletes yielded negligible frame disparities, thus compromising the effectiveness of the frame difference technique in this context. As a result, the analysis of the motion foreground was unsuccessful. Enhancements to the method were made in subsequent trials by adopting the frame difference accumulation approach for the detection of athletic postures, which proficiently pinpointed the regions of posture transition in weightlifting athletes [16]. In instances of low-resolution training videos, the changing space model of optical flow was employed to identify athletic postures. Here, the results of optical flow tracking laid the groundwork for channel direction establishment, segmenting the weightlifting activity into phases of squatting, descending, and standing [17].

2.3 Model of human posture features

In the realm of sports training, the formulation of a human posture feature model is instrumental for the identification and verification of weightlifting athletes based on distinct posture characteristics [18]. Such characteristics, encompassing exertion, apex reach, and squatting, are quantified through ratios of contour width to height, human body rectangularity, width-to-length ratio, perimeter squared-to-area ratio, and posture feature angles across four quadrants, culminating in the establishment of a posture feature model tailored for weightlifting athletes [19]. To discern between athlete and non-athlete targets, a BP neural network training strategy is employed, leveraging its renowned efficacy and precision in prediction, calibrated via mean square error (MSE) [20]. Mastery over the BP neural network classifier's training steps is achieved to facilitate the detection of athletic postures, thereby laying the groundwork for refining sports training methodologies. In the classifier's testing phase, weightlifting posture data are inputted, necessitating computational output from both hidden and output layers due to the algorithm's classification nature. Upon completing the test training with all samples, the classifier unveils the results of weightlifting athletic posture recognition alongside the corresponding accuracy rate [21].

3. Results and discussion

3.1 Experimental results

A collection of 350 videos capturing three distinct postures of weightlifting athletes during training sessions was amassed utilizing a camera. The statistical analysis, predicated on the BP network model for human posture recognition, yielded the results presented in Table 1.

Table 1. Experimental results for weightlifting athlete posture recognition

Posture category	Videos	Correct detection	Accuracy (%)
Exertion	280	275	98.21
Reaching the highest point	280	280	100
Squatting	280	280	100

Examination of the tabulated data reveals that the accuracy rate for the recognition of the exertion posture is marginally reduced to 98.21%, a discrepancy potentially attributable to extrinsic perturbations and the nuanced variance between movements that precipitate misjudgments. Conversely, the accuracy rates for identifying the postures of reaching the zenith and squatting are markedly higher, with both achieving the pinnacle of precision at 100%.

3.2 Method optimization

3.2.1 Necessity

In the intricate milieu of sports training, characterized by a plethora of participants and a heterogeneity of training schemata, objectives, and methodologies, the task of detecting athletic postures is rendered more arduous. A paramount challenge is the homogeneity observed amongst frames. Specifically, in the context of weightlifting training, the presence of barbells may occlude portions of the athlete's movements, thereby impinging upon the precision of key frame extraction and elucidating the aforementioned issue of frame congruence. The categorization of weightlifting postures during the detection process presents its own set of hurdles, stemming from illogical classification demarcations and pronounced disparities in classification ratios, which in turn affect the veracity of the detection outcomes. Consequently, the augmentation of data through methodological refinement is imperative. This entails the meticulous delineation and annotation of target posture categories, culminating in the genesis of a robust target posture dataset. This dataset, buttressed by the BP neural network, is designed to bolster sports training efficacy and furnish precise guidance for the execution of athletic postures [22].

3.2.2 Applicability of the poselet method

The poselet keyframe extraction methodology is employed to discern pivotal athletic postures in weightlifting athletes, predicated on the extraction of samples anchored in stringent spatial configurations and the scrutiny of image attributes, thereby facilitating expeditious and precise posture detection. Within the ambit of weightlifting training footage, salient locales and movement magnitudes are pinpointed, and the poselet detector is deployed with stability to dynamically seize detection points. These points are then aggregated for focused examination. The training regimen is analytically segmented into five distinct phases—knee extension, knee flexion, exertion, squatting, and standing (culminating in the highest point)—each meticulously observed for the exertion and velocity of movements, thereby enriching the dataset and culminating in the accurate identification of essential weightlifting postures.

3.2.3 Key points in the application of the poselet method

Anchored in statistical learning theory, the detection of key weightlifting postures commences with the SVM classifier's inaugural training, aiming for structural risk minimization and global optimization. Upon the video frame's input, the foreground is discerned, succeeded by a multi-scale scan. A tally of detection windows ensues, aggregating data to ascertain the optimal key frames, thus refining the SVM posture classifier's training and mitigating frame similarity concerns [23]. The methodology initiates with the delineation of the histogram of oriented gradients within a rectangular frame, engendering image feature descriptors. The ensuing phase encompasses gradient computation, treating training set samples as discrete channel images. The computation of pixel point direction gradients' magnitude involves independent assessment of each component, with the component's maximal value designated as the gradient direction. Subsequent to spatial difference scrutiny, normalization, and feature vector acquisition, the moving images undergo recurrent gradient calculations until the image features are fully materialized.

The process of image feature extraction is illustrated in Figure 3 .

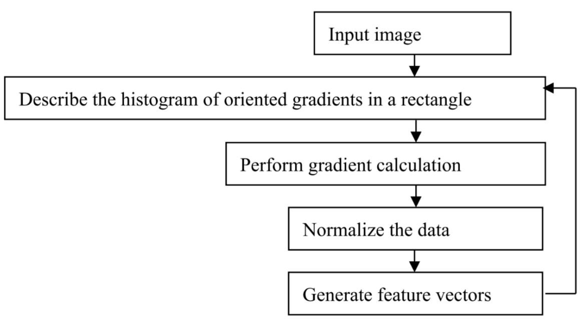

Figure 3. Process of image feature extraction

Grasping the principles of weight distribution is paramount. Application of Gaussian filtering to the gradient windows within image regions precedes the computation of the regional gradient histogram, with weight selection being contingent upon the Gaussian function's configuration. Within the image subspace, weights are conferred in accordance with spatial proximity.

A total of 95 positive and 430 negative samples from weightlifting training were procured, encompassing a diverse array of training milieus to ensure a broad spectrum of athletes and barbell masses. Defining the region size with precision is vital to expedite the detection of athletes' movements while maintaining accuracy, with the objective of amassing a comprehensive collection of dissimilar postures. Utilizing these samples, an SVM classifier is calibrated to discern distinct athletic postures by scrutinizing video images across varied scales and orientations. Given the propensity for multiple postures to encompass erroneous ones, enhancement training is imperative. This necessitates meticulous sifting and excision of detection windows, coupled with the SVM classifier's recalibration to pinpoint pivotal weightlifting postures [24]. Subsequent to this process, individual SVM classifiers for each posture undergo training, succeeded by a multi-scale examination of training videos. The scale parameters are set as follows:

ScaleO=0.65: Initial scale, scaled down to half of the image

Scalestep=1.025: Scaling step

Scalemax=30: Maximum scaling

In the domain of weightlifting training video analysis, key postures are ascertained via horizontal and vertical scanning modalities. Diverging from antecedent multi-scale target detection methodologies that necessitated result clustering for target localization, the present approach entails the documentation of detection points for each video frame independently, obviating the requirement for clustering [25]. This paradigm shift engenders a substantial diminution in the error rate, concurrently augmenting the precision of detection outcomes. Sequential extraction and identification of key athletic postures within weightlifting training videos are conducted, with the inaugural key posture frame being determined by the zenith of detection points. A null detection point count signifies the optimality of the chosen key frame, thereby eliminating the necessity for subsequent detection iterations. The ensuing detection of key posture frames adheres to an analogous protocol, cumulatively enhancing detection alacrity and efficacy [26].

To discern quintessential postures such as knee extension, knee bending, exertion, squatting, and standing, a quintet of posture classifiers has been meticulously trained. The training corpus comprises 260 weightlifting training videos, while the test corpus encompasses 140 video sequences. Pertaining to each posture, 180 positive exemplars are extracted and subsequently augmented to 360 via horizontal mirroring, supplemented by 120 arbitrarily selected negative samples. The empirical outcomes for both the training and test sets are delineated in Table 2.

Table 2. Experimental results for test and training sets

Set category	Posture	Number of videos	Number of correct detection
Training set	Knee extension	260	260
	Knee bending	260	260
	Exertion	260	260
	Squatting	260	260
	Standing	260	260
	Total	1300	1300
Test set	Knee extension	140	140
	Knee bending	140	140
	Exertion	140	140
	Squatting	140	140
	Standing	140	140
	Total	700	700

The tabulated data manifestly demonstrates that the training and test cohorts, delineated for the pivotal weightlifting postures and predicated on the poselet keyframe extraction paradigm, evince an ostensibly impeccable detection of the exertion posture within the test ensemble, corroborated by the empirical count of 140 videos. Such findings bespeak the heightened precision inherent in the identification of the quintet of motion postures. Collectively, this methodology is deemed efficacious for the rectification of analogous motion postures interspersed among image frames in athletic training scenarios [24].

3.2.4 System implementation

The investigation delineates the deployment of annotated data within sports training contexts, culminating in the adept recognition of weightlifting athletes' postures. The analysis reveals that the network excels in posture detection accuracy, boasting ease of deployment, operation, and efficiency [27]. The advent of AI in athletic posture detection is a discernible trend within sports training. An automatic detection system for video image keyframes, predicated on the discussed methodologies and experimental insights, is proposed. This system integrates the frame difference approach, poselet keyframe extraction technique, and a BP neural network, with the objective of distilling essential athletic posture data from weightlifting activities [28]. It encompasses modules for video playback, keyframe extraction, and the exhibition of pivotal athletic postures. The principal interface is partitioned into distinct zones, including areas for video playback, keyframe visualization, and functionality, catering to the requisites of video frame segregation, keyframe immobilization, and data conveyance. The utilization of this system by sports coaches necessitates the annotation of additional datasets, attributable to the intricacies inherent in authentic training environments [29]. Moreover, the disparity in category proportions within the classification of weightlifting athletes' postures in real-world training scenarios is addressed by augmenting the data corpus and employing data augmentation tactics for infrequent categories, such as initiation and cessation states, thereby facilitating the poselet method's application. Coaches are thus enabled to furnish bespoke guidance, predicated on individual detection data, and to refine training regimens accordingly, enhancing both the precision and aesthetic of weightlifting postures, which substantially amplifies training efficacy and propels athletes towards stellar competitive performances [30].

4. Conclusions

The detection of athletic postures has emerged as a foundational element in sports training. Within the realm of sports videos, the heterogeneity of information pertaining to athletic postures is particularly pronounced in competitive sports, necessitating the precise detection of such postures to inform training directives. Current advancements in AI-based detection technologies, predicated on image analysis and video processing, not only furnish coaches with supplementary tools during training sessions but also amplify viewers' engagement by highlighting key athletic posture frames. This holds especial significance in the discipline of weightlifting, which demands elevated technical prowess. The synergistic application of frame difference methods, poselet keyframe extraction, and BP neural networks facilitates the meticulous extraction and robust analysis of key athletic postures, thereby providing cogent evidence for the refinement of weightlifting techniques. The salient contributions of this study are encapsulated as follows:

(1) The introduction of the frame difference algorithm is predicated on the exigency for localized computation of athletic posture data and the expediency of keyframe acquisition in sports training. An embedded AI-based detection and recognition system, augmented by microprocessors, is posited. This system operationalizes frame difference, aligning with the environmental perception and human-machine interaction exigencies of weightlifting training.

(2) The frame difference method is rigorously applied through experimental analysis. Interference factors in foreground area detection often obfuscate weightlifting postures. A series of experiments, encompassing the binarization, erosion, and dilation of grayscale images, have been conducted to elucidate the contours of weightlifting postures. Concurrently, multi-channel tracking algorithms have been deployed for motion statistical analysis, earmarking key frames indicative of the apex of motion, exertion, and squatting postures.

(3) The establishment of a human posture feature model predicated on the BP neural network: A model, informed by the distinctive features of athletic postures, has been developed to facilitate the identification of target postures in weightlifting athletes, thereby contributing to intelligent sports training.

(4) The refinement of the poselet keyframe extraction method: Informed by a motion posture training classifier, this method expeditiously and precisely discerns athletic postures within sports training videos, effectively addressing the issue of frame-to-frame similarity and yielding commendable detection outcomes.

Limitations and Prospective Trajectories: The author acknowledges constraints in theoretical research breadth and the assemblage of sports training materials, coupled with a nascent familiarity with the innovative applications of AI in the detection of athletic postures. Future research endeavors should endeavor to augment the theoretical framework and amass a comprehensive array of sports training materials, thereby underpinning the study with robust theoretical and empirical support. Moreover, staying current with the evolving landscape and practical applications of AI in athletic posture detection is imperative, particularly concerning the precision of posture detection in sports training. Advancements in target matching across frames and the prognostication of motion intentions are anticipated to standardize and enhance the efficacy of training guidance.

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