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The Educational Value and Role of Dance Rhythm in the Psychological Development of Infants and Young Children from the Perspective of Physical and Mental Science

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SUMMARY: *Dance is one of the significant avenues of releasing feelings, relieving internal stress, and conveying psychological moods in a free-body form. It is also a source of physical and mental regulation. This paper will identify first the main keypoints of infants and toddlers in dance-rhythm activities by entering images into a gesture recognition network. The body parts of infants and toddlers are further identified using the contour values of key-points based on a residual network, and the final categorization of dance movements is done using both key-point features classification and image classification. The identified dance actions are then fed into the Logical-Psychological Cognitive Model (LPCM) and, in combination with features derived using PoISAR images, they are used to assess cognitive-psychological significance and identify the mental state of infants and toddlers with various dance-rhythm postures. The simulation findings indicate that the ratio of intersections of the gesture-recognition estimation algorithm developed in this paper remains within [0.5, 1.0] with an average of 0.951, meaning that the suggested dance-gesture detection algorithm is very practical and applicable in detecting dance rhythms of infants and toddlers. Following the dance-rhythm intervention, the experimental group registered a high degree of improvement, and the overall physical self-esteem score increased to 77.07 from 67.22. It can be seen that psychological intervention with dance helps to increase the physical self-esteem of infants and toddlers, whereas dance rhythm has a positive influence on their mental health development and hence it is clearly pedagogical in nature.*

KEYWORDS: *LPCM model; residual network; PolSAR image; dance rhythm; infant and toddler psychological state*

1 Introduction

Infancy is a very important stage in a child's development, and the experience of this stage will have a profound impact on his or her future development [1, 2]. During this stage, physical activities can play an important role in the psychological development of infants and toddlers, and compared with some other physical activities, dance rhythms have a greater attraction to children and can meet the needs of children's early development [3-6]. Especially in the perspective of physical and mental science, early dance movement can help enhance the

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physical coordination ability of infants and young children, thus improving their mental health development, including self-confidence, mental toughness, etc., which has an important educational value and role [7-10].

Specifically, the educational value and role of dance rhythm for infants and young children are mainly reflected in the promotion of circulatory and respiratory system development, improve body awareness and control, promote cognitive development and intellectual enhancement [11, 12]. Dance rhythm requires infants and young children to keep moving, accelerates blood circulation, promotes the development of heart and lung function, and through dance rhythm, it can cultivate infants and young children's good breathing habits and improve their physical endurance and fatigue resistance [13-15]. Secondly, dance rhythm requires infants and young children to maintain awareness and control of the body at all times, through dance rhythm, infants and young children can improve the perception and control of the body, and develop good body coordination and self-regulation [16-18]. In addition, dance rhythm requires children to imitate and memorize constantly, which can promote the cognitive development and intellectual enhancement of infants and young children, improve observation, thinking ability and judgment, and cultivate logical thinking and creative thinking [19-21]. By cultivating the above comprehensive qualities of infants and toddlers is conducive to the subtle promotion of their psychological development, including willpower, emotional expression, inspiration and imagination [22, 23].

The posture-recognition network is used in this research to record and classify the dance poses of infants and young children in rhythmic exercises by three subsequent steps consisting of posture recognition, key-point features extraction, and movement classification. Following the identification of the rhythm movements, a LPCM is formed along with the properties of PoISAR images to differentiate the psychological conditions of infants and toddlers based on dance postures. The fuzzy-inference operation is subsequently performed using confidence levels, the least value of the error function is considered as the optimization goal, and the neural network is trained to attain such a minimum target. In addition, target probabilities are calculated by introducing D-S theory, and the extent to which evidence supports a particular conclusion is measured by the support degree of rules. The final target detection result is achieved by combining rules and fusing decisions, enabling the identification of the psychological state of infants and young children in various dance-rhythm postures. A Kinect-based simulation environment is also created to test the effectiveness of the gesture-recognition network. Once verified, the model is used to implement practical detection of the psychological states of infants and toddlers in the process of dance-rhythm action and the evaluation of the educational value and psychological significance of dance rhythm in this age category.

2 Dance rhythm detection based on pose recognition

2.1 Dance rhythm detection

2.1.1 Pose Recognition Network

Figure 1 shows the structure of the pose recognition network. Branch 1 is the key-point heatmap branch and it mostly predicts the positional confidence map SSS, and Branch 2 is the limb vector branch and it is primarily tasked with the prediction of the component affinity field L.

The iterative estimation takes place in the pose-recognition network, and the corresponding prediction process is represented by Eqs. (1) and (2).

$$S^t = \rho^t(F, S^{t-1}, L^{t-1}), \forall t \geq 2 \tag{1}$$

$$L^t = \Phi^t(F, S^{t-1}, L^{t-1}), \forall t \geq 2 \tag{2}$$

where ρ, Φ represent the convolution operations associated with the S branch and the L branch, respectively. To prevent gradient disappearance during network training, a loss term is generally introduced into the computation, as given in Eq. (3):

$$f = \sum_{t=1}^{T}(f_x^t + f_L^t) \tag{3}$$

$$f_x^t = \sum_{j=1}^{J}\sum_{p} W(p) \cdot \left\| S_j^t(p) - S_j^*(p) \right\|_2^2 \tag{4}$$

$$f_L^t = \sum_{c=1}^{C}\sum_{p} W(p) \cdot \left\| S_c^t(p) - S_c^*(p) \right\|_2^2 \tag{5}$$

where f_x^t, f_L^t denote the estimated values of the key-point confidence maps and PAFs, respectively, whereas S_j^*, L_c^* represent their corresponding ground-truth values. The true confidence maps generated through the maximum operation can be used to obtain the maximum value of the individual confidence map S_{jk}^* for the k-th person at position j, as shown in Eq. (6):

$$S_j^*(p) = \max_k S_{jk}^*(p) \tag{6}$$

$$S_{jk}^*(p) = \exp\left(-\frac{\left\| p - x_{ik} \right\|_2^2}{\sigma^2} \right) \tag{7}$$

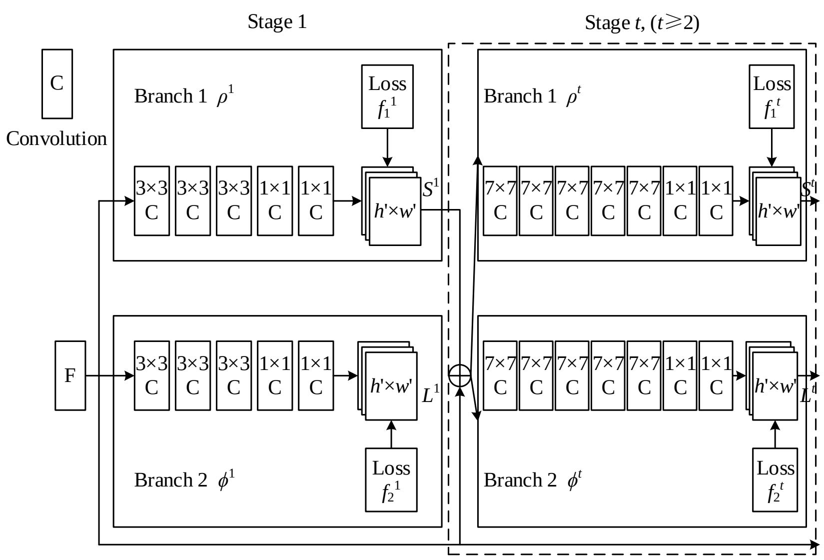


Figure 1: Posture recognition network structure

2.1.2 Dance Rhythm Detection Based on Posture Recognition

The dance movement detection process using the pose recognition approach in this study has been divided into three modules, which are posture identification, key-point feature processing, and movement category judgment. The input image is scaled to 368x368 first and then fed into the pose recognition network to detect the key points of infants and children. Then, infant area is identified by the contour information of the infant key points using residual network processing. Lastly, dance movement categories are determined by combining key-point feature classification with image-based classification. The entire process of dance action detection through pose recognition is shown in Fig. 2, and the joint-point classification network comprises three main paths namely key-point feature extraction, image recognition, and feature fusion.

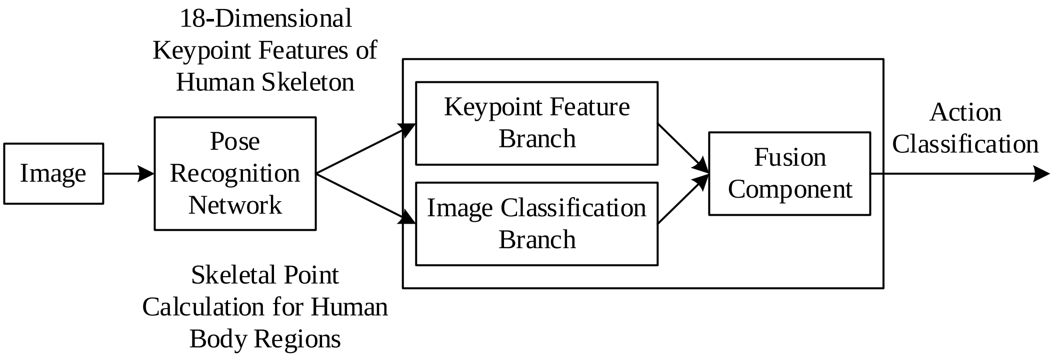


Figure 2: Dance movement detection process based on pose recognition

The fully connected structure is planned within the key-point feature classification path with six layers based on the analysis of the dance action feature characteristics. The number of neurons in the first layer is equal to the dimensionality of the key-point feature output that is derived using pose recognition, i.e. 18. There are 256 neurons in the second layer and 512 neurons in layers 3 to 6.

In the residual-block image classification path, convolutional layers and batch normalization layers are used to build residual units, and several residual units are combined into a residual network. It is this structure that allows the network to learn all the functions. The experiments have demonstrated that direct residual learning may simplify the model. So, the residual units offered by ResNet are the ones trained on the neural network, and a dropout layer is added between the third and fourth layers. First, the input image is cropped to 368x368 and the infant contour box is obtained based on the key-point contour values to be used in training ResNet50. ResNet50 has four residual blocks and the size of the preprocessed image is 224x224. The training process is explained in detail below:

Step 1: The preprocessed image goes through a 7x7x64 convolutional layer with a stride of 2 to produce an 112x112 feature map.

Step 2: The resulting feature map is then passed through a 3x3 pooling window with a stride of 2 and sequentially through three residual blocks. These blocks have three convolutional layers, which are 1 x 1 x 64 (first layer), 3 x 3 x 64 (second layer) and 1 x 1 x 256 (third layer).

Step 3: Once residual unit processing is done, the output is forwarded to an average-pooling layer.

Finally, in step four, two fully connected layers of 2048 and 512 neurons are sequentially connected.

2.2 Psycho-cognitive judgment of dance rhythm

Chapter 2.1 detects the dance rhythm. Next, based on the known characteristics of PolSAR images and in combination with the psychological cognitive process of professional image judges in interpreting PolSAR images, the characteristics of different interpretation requirements will be analyzed, and a "logical-psychological" cognitive model (LPCM) including "fuzzy reasoning - comprehensive decision-making" will be constructed. Realize intelligent ground object interpretation and automatic target detection of high-resolution PolSAR images.

2.2.1 Establishment of a “logical-psychological” cognitive model

The input image is filtered to remove coherent noise. After filtering, the input image is divided into two processing lines: feature extraction based on target cues and feature extraction based on contextual cues, which simulate the bottom-up and top-down processing modes in the cognitive processing of images in the infant brain, respectively. The left line first extracts the selected n polarized features $f_1, f_2, \cdots, f_n$, and then determines the weights $w_1, w_2, \cdots, w_n$ of each feature based on the guidance of the a priori knowledge, and enhances or suppresses the corresponding features according to the weights. features to obtain the target region map F_t based on target cues:

$$F_t = w_1 f_1 + w_2 f_2 + \cdots + w_n f_n \tag{8}$$

The region map based on contextual cues also determines the environment where the target is located based on a priori knowledge, and then extracts the contextual feature f_c to get the contextual region concern map F_c. Finally, the two region maps are merged to get the target region F.

$$F = F_t \cap F_c \tag{9}$$

2.2.2 Confidence-based fuzzy inference process realization

There exists an N-dimensional sample space R^n, where $X = \{X_1, X_2, \cdots, X_N\} \subset R^n$, denoting the set of all pixel point feature vectors. And there are $\forall k, 1 \le k \le N$, $X_k = (x_{k1}, x_{k2}, \cdots, x_{kn})^T \in R^n$, denoting the feature vectors represented by the combination of n features of the pixel point x_k, $x_{kj}(j = 1, 2, \cdots, n)$ denoting the pixel point x_k the jth feature of pixel point x_k, and $V^T = (V_1, V_2, \cdots, V_c)(V \in R^n, i = 1, 2, \cdots, c)$ denotes the center vectors of different categories. The existing error formula $J(U,V)$, in this paper, the size of the calculation of the confidence level is transformed to find the U and V that ensure the minimum value of the error function, the specific expression is shown in (10):

$$J(U,V) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j}^{n} u_{ij}^m d_{ij}^2 \tag{10}$$

where u_{ij} refers to the confidence that the pixel point x_j is judged to belong to the ith class, and $m \in [1, +\infty)$, is a weighted index:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, \cdots, n \tag{11}$$

$$d_{ij} = \left\| v_i - x_j \right\| = (v_i - x_j)^T (v_i - x_j) \tag{12}$$

The necessary conditions to minimize Eq. (10) can be found by constructing a new error function as follows:

$$\begin{aligned} \bar{J}\left(U, v_1, \ldots, v_c, \lambda_1, \ldots, \lambda_n\right) &= J\left(U, v_1, \ldots, v_c\right) + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} u_{ij} - 1 \right) \\ &= \sum_{i=1}^{c} \sum_{j}^{n} u_{ij}^m d_{ij}^2 + \sum_{j=1}^{n} \lambda_j \left(\sum_{i=1}^{c} u_{ij} - 1 \right) \end{aligned} \tag{13}$$

where $\lambda_j (1 \le j \le n)$ is the Lagrange multiplier of the n constraints of equation (10). Derivation of Eq. (13) for all variables yields U and V that minimize the error function:

$$\begin{cases} u_{ij} = 1 \Big/ \sum_{k=1}^{c} \left(d_{ij} / d_{kj} \right)^{2/(m-1)} \\ v_i = \sum_{j=1}^{n} u_{ij}^m x_j \Big/ \sum_{j=1}^{n} u_{ij}^m \end{cases} \tag{14}$$

2.2.3 Neural network based target detection

A PCN consists of three elements that include the input area, modulation area, and pulse generation area as shown in Fig. 3. The input area accepts two types of information which are feedback input F_{ij} and connection input L_{ij}. Feedback input takes the input signal S_{ij} along with other external signals and connection input is the interaction between neurons. Modulation area regulates the connection input and mixes it with the feedback input using a product operation. Pulse generation area is primarily created by a variable-threshold comparator and a pulse generator.

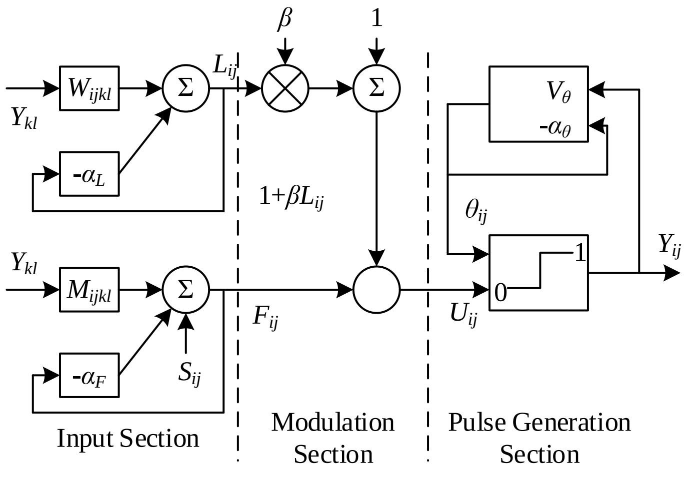


Figure 3: PCNN neuron model

The specific mathematical model is shown in equation (15):

$$\begin{cases} F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{kl} m_{ijkl} Y_{kl}[n-1] + S_{ij} \\ L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} w_{ijkl} Y_{kl}[n-1] \\ U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \\ Y_{ij}[n] = \begin{cases} 1, U_{ij}[n] > \theta_{ij}[n-1] \\ 0, otherwise \end{cases} \\ \theta_{ij}[n] = e^{-\alpha_\theta} \theta_{ij}[n-1] + V_\theta \sum_{kl} Y_{kl}[n-1] \\ \alpha_F < \alpha_\theta < \alpha_L \end{cases} \tag{15}$$

where, $F_{ij}[n]$ - the n th feedback input of the (i, j) th PCN.

$L_{ij}[n]$ - connection input.

S_{ij} - neural network external input.

W, M - connection weight matrix, representing the connection strength between each neuron.

$U_{ij}[n]$ - modulation domain output.

$Y_{ij}[n]$ - output pulses.

$\theta_{ij}[n]$ - Dynamic threshold, varying with.

V_F, V_L, V_θ - intrinsic potential, usually $V_L = 1, V_\theta$, V_θ as large as possible.

$\alpha_\theta, \alpha_F, \alpha_L$ - time decay constant.

β - connection coefficient, $\beta \in (0,1)$.

The specific working principle is as follows: when the modulated signal $U_{ij}(n)$ is greater than the dynamic threshold $\theta_{ij}(n)$, the pulse generator will produce a pulse $Y_{ij}(n) = 1$, the neuron belongs to the activation state, known as a time of ignition, at this time, the dynamic threshold also through the feedback along with the sudden increase. When the dynamic threshold is greater than, the pulse generator stops outputting pulses, the dynamic threshold begins to decay exponentially, and when $\theta_{ij}(n)$ is less than $U_{ij}(n)$, it outputs a pulse again, and so on and so forth, making the neuron issue pulses at a certain period.

2.2.4 Calculation of target probability based on evidence theory

D-S theory is constructed on a non-empty finite set Θ, which is referred to as the frame of discernment, namely the collection of all possible outcomes that can be identified for a given problem. Let Θ denote the discernment framework. If a set function $m: 2^\Theta \to [0,1]$ satisfies $m(\varnothing) = 0; \sum_{A \in \Theta} m(A) = 1$, then $m(A)$ represents the confidence assigned to A within the discernment framework, and it is known as the Basic Probability Assignment function, abbreviated as BPA. Its definition is given below:

$$m(A)=\frac{\sum_{B_j\cap A_i=A}\prod_{\substack{j=1\\i=1}}^{n,q}m_j(A_i)}{1-\sum_{B_j\cap A_i=\varnothing}\prod_{\substack{j=1\\i=1}}^{n,q}m_j(A_i)} \tag{16}$$

where $B_j\left(j=1,2\cdots n\right)$ and $A_i\left(i=1,2,\cdots q\right)$ are the focal elements of the basic probability assignment function, respectively, and $B_j\cap A_i=\varnothing$ denotes the fiducial mass assigned to the empty set, and $B_j\cap A_i=A$ denotes the total fiducial mass assigned to A.

On this basis and derived from two functions - confidence function (Bel) and likelihood function (PI), the formula is shown below:

$$\begin{aligned}
&Bel(A)=\sum_{B\subseteq A}m(B)\\
&Bel(\varnothing)=0\\
&Bel(\Theta)=1\\
&PI(A)=1-Bel(\bar{A})=\sum_{B\cap A\neq\varnothing}m(B)\\
&PI(A)\geq Bel(A)
\end{aligned} \tag{17}$$

From the formula, we can know that the confidence function indicates the degree of trust in the evidence for the question A is true, the likelihood function (PI) describes the degree of trust in the set for non-false, also known as the irrefutable function or the upper limit function. The confidence function $Bel\left(A\right)$ and the likelihood function $PI(A)$ are the lower and upper bounds of the trust in A, respectively, and can be written as $[Bel(A),PI(A)]$.

2.2.5 Decision fusion based on combinatorial rules

Let the set of rules R matching the actual goal be:

$$R=\left\{X_1\Rightarrow Y_1,X_2\Rightarrow Y_2,\cdots,X_n\Rightarrow Y_n\right\} \tag{18}$$

for any subset R_i of the set of rules:

$$R_i=\left\{X_{i1}\Rightarrow Y_{i1},X_{i2}\Rightarrow Y_{i2},\cdots,X_{im}\Rightarrow Y_{im}\right\} \tag{19}$$

where $1\leq i_1,i_2,...,i_m\leq n$. If the following conditions are satisfied:

(1) $X_{i1}=X_{i2}=...=X_{im}$.

(2) $Y_{i1}\neq Y_{i2}\neq...\neq Y_{im}$.

That is, all the rules in R_i have the same preconditions (knowledge), and the conclusions obtained based on the knowledge are different, at this time can be regarded as an expert.

Let the set of credible probabilities corresponding to all the rules in the set be $conf_i=\left\{conf_{i1},conf_{i2},\cdots,conf_{im}\right\}$. From the perspective of decision making, the credible probabilities of the rules can be understood as the degree of trust of the decision maker to draw the corresponding conclusions according to the knowledge he/she possesses. Therefore, $conf_i$ can be regarded as the credible probability assignment of experts to different decision outcomes $\{Y_{i1}, Y_{i2}, \cdots, Y_{im}\}$ according to X_{ij}. In this way, an expert set $\{R_1, \cdots, R_i, \cdots, R_j, \cdots, R_t\}$ and its corresponding trusted probability assignment, $1 \le t \le n$, can be obtained and satisfied:

From the above two equations, it can be seen that the opinions of experts can not only fully utilize the full range of valid rules obtained, but also convert n matching rules into t independent experts, so that the evidence provided by t experts, $(1 \le i \le t)$ can be effectively synthesized.

In this paper, we measure the degree of support for the evidence by the support of the rules. Let the support of a rule in an expert be:

$$sup_i = \{sup_{i1}, sup_{i2}, ..., sup_{im}\} \tag{20}$$

In this paper, we derive the weight of evidence from the perspective of rule support by the following equation based on the principle of maximum support:

$$imps_i = \max sup_i = \max\{sup_{i1}, sup_{i2}, ..., sup_{im}\} \tag{21}$$

From the above analysis, it can be seen that if a certain feature evidence is important, then the decision made based on that feature evidence has a high credible probability. Therefore, this paper defines the weight of evidence as follows:

$$\omega_i = \frac{imps_i}{\sum_{j=1}^{t} imps_j} \tag{22}$$

The unknowable part of the trusted probability assignment is divided into two parts: unknowable due to weight assignment and unknowable due to incomplete image information acquisition. The decision rule adopted in this paper is as follows:

For a certain target to be tested, let the set of experts matched with it be, and the corresponding weight of evidence and credible probability assignments are $W = \{\omega_1, ..., \omega_i, ..., \omega_j, ..., \omega_t\}$ and $CONF = \{conf_1, ..., conf_i, ..., conf_j, ..., conf_t\}$, when $t > 2$, firstly, fusion of $\omega_1 \times conf_1$ and $\omega_2 \times conf_2$ is performed, and then the synthesized result is fused with $\omega_3 \times conf_3$, and so on, for two-by-two fusion until a synthesized plausible probability assignment for t pieces of evidence is obtained. According to the final credible probability assignment, the corresponding decision result can be derived according to the combination principle.

From this, the decision fusion formula can be obtained:

$$\begin{aligned} &m(M_c) = \max\{m(M_i)\} \\ &m(M_c) - m(M_i) > \lambda_1 \\ &m(\Omega) < \lambda_2 \\ &m(M_c) - m(\Omega) > \theta \end{aligned} \tag{23}$$

where M_c is the detected target, M_i is each category of features, $m(\Omega)$ is the uncertainty probability of the target, and λ_1, λ_2 is the set threshold.

The BPA corresponding to each feature is calculated using the improved SVM, and then the decision fusion is performed using the combination rule to realize the final detection of the target and identify the mental state of infants and children in different dance rhythmic postures.

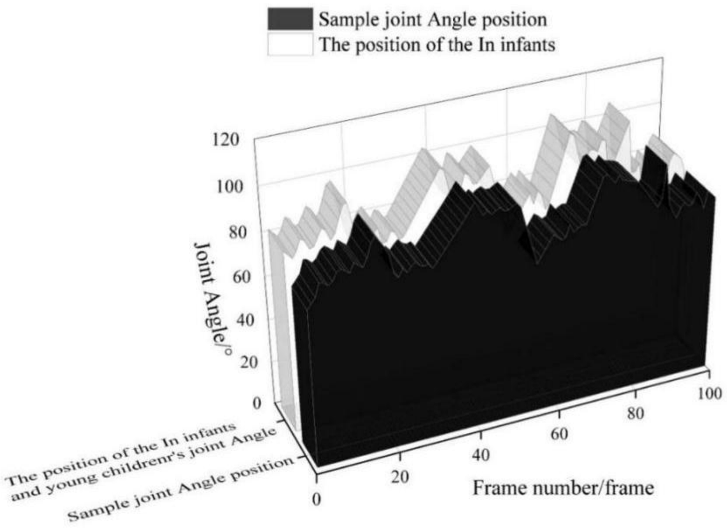
3 The educational value and role of dance movement in the psychological development of infants and young children

3.1 Model Detection

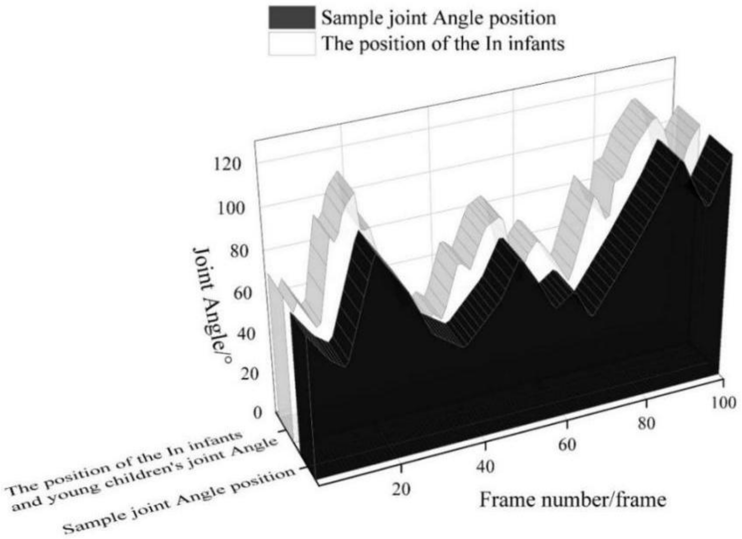
3.1.1 Dance rhythm test

The experimental setup was built using MATLAB and Kinect 2.0 on a computer with an Intel Core i7 processor and a 500 GB hard disk. In order to assess the detection accuracy of the dance posture recognition network as proposed in the present paper, two observation objects were chosen: joint angle 1, which is formed between the left shoulder, left elbow, and left wrist, and joint angle 2, which is formed between the right hip, right knee, and right foot.

The outcome of the testing of every joint angle is illustrated in Fig. 4, with joint angle 1 depicted in Fig. (a) and joint angle 2 in Fig. (b). Between 0 and 100 frames, the movement path of joint angle 1 in infant dance movements is generally similar to the respective path in the sample library, and the largest deviation does not exceed 10 degrees and average error is -1.04. The path of joint angle 2 inside the same interval of frames also corresponds to the same position of the sample library. In infant dance actions, the variation tendency of joint angle 2 is still consistent with the sample path but the deviation detected during the action at around the 74 th frame near the trainer is relatively large when the error is 19.17 and the total error is 4.64. Such findings suggest that the model developed in this paper would be able to correctly recognize the rhythm of dance movements made by infants and children. The model may also be used to facilitate correction of movements by comparing detected actions with actions stored in the sample library.



(a)Test results of joint Angle 1



(b)Test results of joint Angle 2

Figure 4 Test results of each joint Angle for female

3.1.2 Comparison of indicators

The accuracy of the detection result of infant dance gesture movement is considered when the intersection-over-merger ratio is between [0.5, 1.0]. Closer to 1.0 is a higher precision of the detection, and less than 0.5 means that there is an error in detecting the infant dance gesture movement. Six separate groups of dance posture movement segments were found. The three detection methods were applied to determine the intersection and concurrency ratios which were subsequently analyzed using MATLAB simulation software. The outcomes are illustrated in Fig. 5. The movements indicated by ZT-01 to ZT-06 are knee bending, big kick, spinning circle, toe crouching step, Bray dance step, and toe drawing circle respectively.

The detection results obtained by the three methods show evident differences. For the pose recognition estimation method proposed in this paper, all intersection-over-merger ratios are within [0.5, 1.0], and each value exceeds 0.8, with a mean value of 0.951, which is close to 1.0. After the improved ViT method is applied, the intersection and concurrency ratios of dance posture segments 1, 3, 5, and 6 are below 0.5. After using the improved FCN method, the ratios of dance posture segments 1, 3, 4, and 5 are also lower than 0.5. The comparison demonstrates that the dance posture detection method proposed in this study has strong practical feasibility and clear advantages in detection accuracy.

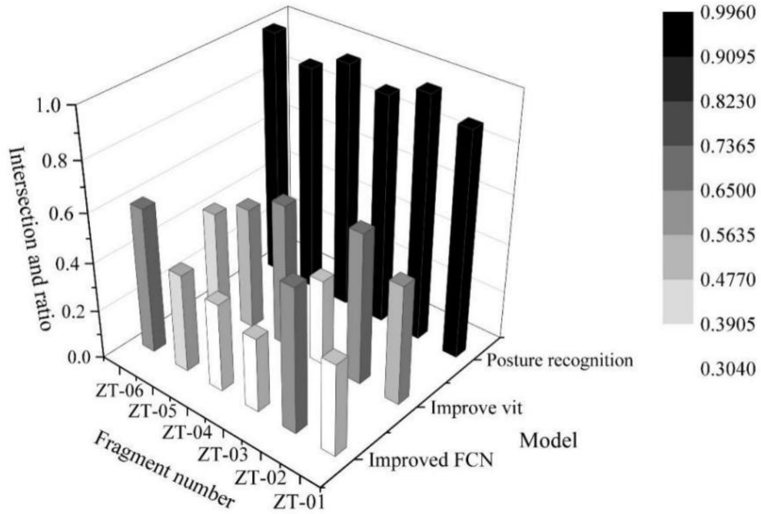


Figure 5: The comparison results of the intersection ratio indicators of the three methods

3.1.3 Analysis of mental representations of dance movements

Table 1 shows the psychological representation judgment of the dance movements, and the cognitive correctness of the emotional affect contained in all four dance movements was higher than 65%. The cognitive sensitivity and correctness of disgust was the highest at 76.77%, and the cognitive sensitivity and correctness of happiness was the lowest at 68.07%. The difference in the correct rate of emotional-emotional cognition between the groups of subjects for the various dance movements for infants and toddlers did not exceed 9%.

Table 1: The psychological representation of dance actions is judged

Group	Correct	Misjudge	Total number	Accuracy
Joyfulness	113	53	166	68.07%
Neutrality	128	42	170	75.29%
Surprise	43	18	61	70.49%
Revulsion	76	23	99	76.77%

3.2 Study design

In this study, we conducted a dance psychology intervention experiment focusing on enhancing the physical and mental health of infants and toddlers by combining dance rhythmic movements with psychological experience to address the physical self-esteem issues of infants and toddlers on the psychological existence of dance rhythms.

Experimental tools:

Based on dance gesture recognition and dance rhythm psychological cognitive judgment.

Experimental prerequisites:

Equal grouping design: preexperimental group = precontrol group = precontrol group. Three classes were randomly selected from Kindergarten Y as the experimental group, control group, and control group. Infants and toddlers in the experimental group were judged by dance posture recognition and dance rhythm mental cognition, and psychological interventions were taken in time for the judgment results. In the control group, the infants and toddlers were taught to improve their physical and mental health through Yi Jin Jing. In the control group, the infants and toddlers were left alone and no intervention was taken.

Expected results of the experiment: one-way ANOVA test for post-test comparison of differences between different groups: post-test of experimental group > post-test of control group > post-test of control group. Paired samples t-test for pre-test and post-test of the same group: post-test of the experimental group > pre-test of the experimental group, post-test of the control group > pre-test of the control group.

3.2.1 Physical self-esteem of infants and young children

Table 2 shows the results of descriptive statistics of physical self-esteem, and the average score of physical self-esteem of infants and young children measured by the model is 72.829, which is slightly lower than that of previous studies. This may be due to the fact that in recent years, the rapid popularization of the Internet has brought many positive influences to the development of infants and young children, as well as many negative influences, such as addictive disorders, physiological syndromes, social isolation, and aggressive behaviors, etc., which greatly affect the formation and development of infants and young children's physical self-esteem. Among them, the lower scores on physical self-worth may be due to the fact that physical development at the kindergarten stage affects the way young children feel and think about themselves, while they have not yet formed a clearer understanding of their personal value, and are prone to lower levels of awareness and satisfaction with their bodies.

Table 2: Physical self-esteem describes statistical results

	Case number	Minimum value	Maximum value	Mean value	Standard deviation
Physical self-value	500	6	24	14.265	3.248
Athletic ability	500	6	24	14.853	3.101
Physical condition	500	6	24	14.639	3.248
Physical attraction	500	6	24	14.536	3.072
Physical quality	500	6	24	14.536	3.185
Total body self-esteem score	500	30	120	72.829	13.504
Effective case number (listed)	500				

3.2.2 Comparative analysis results

In this study, one-way analysis of variance (ANOVA) was used to analyze the differences in the level of physical self-esteem among infants and toddlers in the experimental, control, and control groups before the intervention, and the data obtained are shown in Table 3.

The one-way ANOVA was used to test the significance of the between-group means, and from the perspective of the dimensions of the level of physical self-esteem, although there are some differences in some dimensions of physical self-esteem, the between-group differences of the dimensions did not reach the significant level ($p>0.05$), and the mean values of physical self-esteem of the three groups were 67.22, 66.8, and 68.29, respectively, so the above data indicate that the levels of physical self-esteem of the three groups were basically comparable and had homogeneity before the intervention, and the sample met the requirements of Table 3. Self-esteem levels are basically comparable and homogeneous, and the samples meet the requirements of the experiment.

Table 3: Comparison of pre-test differences among the three groups

Dimension	Group	Number of cases	M±SD	F	P
Sense of physical self-worth	Experimental group	15	12.94±1.42	1.856	0.148
	Compare group	15	12.64±1.42		
	Control group	15	13.64±2.29		
Dance rhythm	Experimental group	15	13.24±1.42	0.415	0.636
	Compare group	15	13.42±1.39		
	Control group	15	13.15±2.14		
Physical condition	Experimental group	15	13.34±1.32	0.748	0.412
	Compare group	15	12.75±1.35		
	Control group	15	13.57±1.87		
Physical attractiveness	Experimental group	15	13.57±1.85	1.296	0.245
	Compare group	15	13.95±2.03		
	Control group	15	14.59±1.42		
Physical fitness	Experimental group	15	14.13±1.96	1.596	0.236
	Compare group	15	14.04±1.68		
	Control group	15	13.34±13.24		
Total score of physical self-esteem	Experimental group	15	67.22±3.63	0.269	0.785
	Compare group	15	66.8±3.24		
	Control group	15	68.29±3.66		

Table 4 compares the pre-test differences across the three groups. To determine whether there were meaningful differences in the average values of physical self-esteem total scores between infants and toddlers in the three groups both before and after testing, one-way ANOVA was used. Following the intervention, the experimental group differed significantly with the control group regarding physical self-worth, dance rhythm, physical fitness, and physical self-esteem total scores. In these dimensions, the mean values of the experimental group were 1.92, 1.31, 1.96 and 5.46, respectively, higher than the control group. Post-intervention experimental group was also significantly different in terms of physical self-worth, dance rhythm, physical fitness, physical attractiveness, and physical strength. In these dimensions, the experimental group surpassed the control group by 1.72, 1.81, 2.11, 1.57, 1.89, and 9.1 respectively. There were statistically significant differences between the intervention group and the control group in the physical condition, physical attractiveness, and total physical self-esteem scores. These results confirm the hypothesis that dance intervention has a positive impact on the experimental group, indicating that dance group exercises might improve physical self-esteem.

Table 4: Comparison of post-test differences among the three groups

Dimension	Group	Number of cases	M±SD	F	P	LSD testing
Sense of physical self-worth	Experimental group	15	15.06±1.52	7.455	0.001**	1>2** 1>3*
	Compare group	15	13.14±1.63			
	Control group	15	13.34±1.82			
Dance rhythm	Experimental group	15	15.05±1.41	8.048	0.002**	1>2* 1>3***
	Compare group	15	13.74±1.42			
	Control group	15	13.24±1.64			
Physical condition	Experimental group	15	15.15±1.34	7.295	0.001**	1>3** 2>3*
	Compare group	15	14.69±2.85			
	Control group	15	13.04±1.58			
Physical attractiveness	Experimental group	15	15.96±1.41	3.966	0.024*	1>3* 2>3*
	Compare group	15	16.15±2.56			
	Control group	15	14.39±2.17			
Physical fitness	Experimental group	15	15.85±1.48	8.748	0.000***	1>2*** 1>3**
	Compare group	15	13.89±2.04			
	Control group	15	13.96±1.45			
Total score of physical self-esteem	Experimental group	15	77.07±1.48	35.148	0.000***	1>2*** 1>3*** 2>3*
	Compare group	15	71.61±3.48			
	Control group	15	67.97±4.59			

Paired-samples t-tests were used in this research to investigate the difference in physical self-esteem and associated levels between the three groups prior to and following intervention and such findings are presented in Table 5.

Through the comparison of pre-test and post-test scores of the experimental group, statistically significant differences were observed between body self-esteem and all dimensional scores of the experiment ($p < 0.05$). The overall body self-esteem score was raised by 77.07 as compared to 67.22. The scores of infants and toddlers in the experimental group after the intervention were significantly higher than those before the intervention which means that dance-assisted psychological intervention can successfully enhance the level of body self-esteem among infants and toddlers.

Paired-samples t-tests were used to compare the pre-test and post-test results of the control group. Physical attractiveness and overall physical self-esteem scores showed significant differences prior to and following the experiment ($p<0.05$). After the experiment, the score rose by 4.81 points indicating a better physical and mental state. Nevertheless, the improvement range was lower in every dimension of physical self-esteem as compared to the experimental group. It means that Yi Jin Jing can also play a role in improving the physical self-esteem of infants and toddlers, although it is less effective than assisting them with the dance. Dance assistance causes a more favorable improvement effect. Paired-samples t-tests were also conducted between the scores of the control group before and after the test. There was no significant difference in the physical self-esteem dimensions or total scores of the control group ($p>0.05$). Dancing rhythm has a beneficial impact on the development of mental health in infants and young children, as well as high educational significance.

Table 5: Results of the paired sample t-test

Dimension	Group	Before intervention	After the intervention	t	P
Sense of physical self-worth	Experimental group	12.94±1.42	15.06±1.52	-6.456	0.000***
	Compare group	12.64±1.42	13.14±1.63	-0.945	0.342
	Control group	13.64±2.29	13.34±1.82	0.748	0.428
Dance rhythm	Experimental group	13.24±1.42	15.05±1.41	-4.452	0.000***
	Compare group	13.42±1.39	13.74±1.42	-0.428	0.648
	Control group	13.15±2.14	13.24±1.64	-0.158	0.936
Physical condition	Experimental group	13.34±1.32	15.15±1.34	-5.845	0.000***
	Compare group	12.75±1.35	14.69±2.85	-1.746	0.101
	Control group	13.57±1.87	13.04±1.58	-0.693	0.469
Physical attractiveness	Experimental group	13.57±1.85	15.96±1.41	-4.428	0.000***
	Compare group	13.95±2.03	16.15±2.56	-3.048	0.004**
	Control group	14.59±1.42	14.39±2.17	0.186	0.816
Physical fitness	Experimental group	14.13±1.96	15.85±1.48	-4.428	0.000***
	Compare group	14.04±1.68	13.89±2.04	0.369	0.745
	Control group	13.34±13.24	13.96±1.45	-1.485	0.156
Total score of physical self-esteem	Experimental group	67.22±3.63	77.07±1.48	-14.248	0.000***
	Compare group	66.8±3.24	71.61±3.48	-4.496	0.002***
	Control group	68.29±3.66	67.97±4.59	-0.548	0.548

3.3 Educational Value and Role of Dance Rhythms in Infant and Toddler Psychology

3.3.1 Relief of somatic complaints

Through dance movements, the physical discomfort of infants and toddlers can be relieved. They can be guided to experience relaxation in a certain order of their bodies, part by part. Accompanied by soothing and peaceful music, infants and toddlers can focus on their own breathing, thereby gradually entering a state of deep relaxation. Infants and toddlers, under the direction of music, perform body movements such as twisting, stretching, expanding, rising and falling, rotating, and leaping in the changes of different rhythms to experience the sense of control and relaxation, tilting and balance, lightness and heaviness of their own bodies. On the other hand, when infants and toddlers do dance exercises, it can promote the endocrine changes of infants and toddlers. After exercise, the brain will produce a substance called endorphin. This brain secretion can make people feel happy and satisfied, so it is also called the "happiness hormone" or "youth hormone". Exercise can stimulate an increase in the secretion of endorphins. Under the stimulation of endorphins, the body and mind of , infants and young children can be in a relatively relaxed and pleasant state, and their feelings of tension and anxiety can be significantly relieved.

3.3.2 Stimulation of physical potentials

Dance movement can play an important and positive role in helping infants and toddlers with persecution to break out of the constraints of their thinking and behavioral patterns, and to break out of the boundaries of their own frameworks and rituals.

Dance movement can be used in a way that is visibly confusing and unsettling for infants and toddlers because there are no fixed combinations of movements, and instead of modeling and imitating old patterns, there is revelation and stimulation that encourages infants and toddlers to have their own creative experiences.

Dance movement makes infants and toddlers complete new movements to feel their corresponding kinesthetic sensations, form new conditioned reflexes and power stereotypes, and ultimately gradually achieve infants and toddlers' awareness and discovery of their own potential. The core of dance movement is to enable infants and toddlers to re-know themselves, discover their own potential, resilience and creativity can be restored, and gradually develop improvisational dance practice this way and infants and toddlers stereotypes, curing, inflexible and not easy to reverse the characteristics of thinking is contradictory and antagonistic to the infant and toddler in the beginning in the improvisation of the dance to their own unawareness of the other self, everyone was born a dancer, and the dance is the most important thing to encourage the infant and toddler to actively participate in the dance. In the treatment, we should encourage infants and toddlers to actively and courageously try to liberate their bound bodies and break all the limitations they have set for themselves, so that they can feel both physical and spiritual freedom.

4 Conclusion

In this study, we propose a dance movement detection algorithm based on pose recognition for infants and toddlers, respectively, pose recognition, key point feature processing, and movement classification. The detected dance poses are converted into PolSAR images, and the mental cognition of the professional adjudicator on the interpretation of PolSAR images is combined to analyze the mental state under different dance poses. The LPCM model, which includes fuzzy inference-comprehensive decision-making, is established to recognize the psychological states of infants and children in different dance rhythmic postures. Characterizing and discriminating the psychological state of dance movements, the correct rate of cognition of emotional feelings contained in the four dance movements was higher than 65%. The cognitive sensitivity and correct rate of happiness was 68.07%, while the difference in the correct rate of emotional-emotional cognition of all categories was not more than 9%, and the model was effective in discriminating the psychological state of infants and young children. Through the before and after test experiments, we analyze the change process of the influence of infant dance rhythm on the psychological state of infants and young children, and the experimental group is 9.1 higher than the control group in the dimension of total body self-esteem score, and the P value is less than 0.05, which is a significant difference, and the dance rhythm has a positive influence on the development of infant mental health, which has an important educational value.

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