

## Research Article

# Human Movement Recognition in Dancesport Video Images Based on Chaotic System Equations

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Received 20 July 2021; Accepted 4 August 2021; Published 17 August 2021

Academic Editor: Miaochoao Chen

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This paper presents an in-depth study and analysis of human action recognition in dancesport video images through chaotic system equations. A novel fractional-order chaotic system model with hidden multistability is constructed. Since this fractional-order chaotic system has no equilibrium point, the equilibrium point stability analysis is not required. The effect of system parameters on the multistability characteristics of the fractional-order chaotic system is investigated in depth by using the control variable method and nonlinear dynamic tools. In addition, the system has a special property of offset incremental control, which makes the system more widely and practically useful in engineering applications. Finally, circuit simulation experiments and hardware circuit experiments are conducted for the fractional-order chaotic system, and the results are consistent with the corresponding theoretical analysis. The system architecture of the mobile augmented reality-based ethnic dynamic art display system is designed, and the system architecture adopts a hierarchical design. The experimental results show that the design method of the mobile augmented reality-based dynamic art display system proposed in this thesis can meet the purpose of expanding the ways of dancesport display, and the system designed in this thesis is customizable and the synthesized images have a high sense of realism.

## 1. Introduction

Chaos theory is one of the most important branches of nonlinear science and one of the greatest achievements in 20th-century physics. The establishment of chaos theory broke the illusion of Laplacean determinism based on the Newtonian paradigm and made people realize that Newtonian mechanics has limitations not only for high-speed motion physics and microscopic particles but also for the study of complex systems composed of multiple elements [1]. Chaos theory is the study of dynamical systems, which refers to the existence of unpredictable, irregular motion in a deterministic dynamical system. Chaos, as a special form of motion in nonlinear systems, is widely found in nature. In recent years, with the continuous exploration of chaos, the study of chaos has been widely involved in various disciplines such as physics, biology, mathematics, electronics, music, and art, making chaos science a modern science with a deep

theoretical background. Chaos science has been a major contributor to the progress and development of society by broadening people's horizons and deepening their knowledge of the natural world [2]. With the study of fractional-order differential equations and the application of chaotic behavior, people then began to pay attention to the control and synchronization of fractional-order chaotic systems and found that fractional-order chaotic systems can better meet our information society [3]. In our rapidly developing era, the popularity of the Internet has made information dissemination faster and communication with each other more convenient but also brings the risk of private information being leaked. How to improve the confidential communication ability of the system is of more interest to everyone [4]. We both want to communicate better with others and worry about our information being leaked [5]. This requires us to study extensively how to improve the confidential communication capability of communication systems and what kind of

systems should be selected for communication propagation. Fractional-order chaotic systems have become a research hotspot due to their wide range of orders, and the unpredictability of the system is more suitable for confidential communication systems [6].

With the rapid changes in science and technology, the use of digital technology to innovatively disseminate traditional culture has received a lot of attention from the cultural and information technology communities. It has greatly broadened people's horizons, deepened people's cognition of the natural world, and made important contributions to the progress and development of society. Compared with traditional methods, the use of digital technology for the preservation of intangible cultural heritage is more efficient and comprehensive in preserving intangible cultural heritage and is also more conducive to the promotion of intangible cultural heritage through Internet channels. At present, the more common methods of digital preservation of dancesport include a video recording of dancers using several digital cameras, but it is difficult to record the body dynamics of dancers in an all-round way in this way, and the editability of the image data obtained by this method is relatively poor. Motion capture technology is a relatively new technology, which can better achieve the extraction and preservation of three-dimensional spatial data of dancesport dancers' postures, so this technology is often used for dancesport digital preservation work.

As an important indicator of ergonomic design, human body parameters can judge whether the design of equipment is humane and provide data reference for the improvement of design solutions, so the study of human body parameter measurement has received increased attention. Traditional manual measurement methods have faced the problem of difficulty in measuring human body dimensions accurately, quickly, and in large quantities. In the context of the rapid development of computer vision and network technology, video-based automatic measurement technology of human body parameters has emerged and has shown a trend of intelligence. This technology integrates key technologies such as computer graphics, sensor technology, and optoelectronic information technology, and the core of its research is to make full use of the useful information conveyed by the video to measure human parameters accurately, quickly, and at low cost. Various human body parameters of the target to be measured can be measured in real time, so the video measurement method saves time and human resources than traditional manual measurement. Compared with the traditional contact body parameter measurement, the automatic video-based body parameter measurement only needs to shoot human action video, which using the human motion information in the video sequence can be measured at any time, but also has the advantages of safety, low cost, high human comfort, and good repeatability. Video-based human body parameter measurement technology can realize large-scale, real-time measurement of the body size of sports, dance, military, and aerospace personnel. These persons under test only need to make designated auxiliary measurement actions in the measurement room to obtain real-time measurement of the target under test. Therefore, the video measurement

method saves time and human resources in comparison to the traditional manual measurement. In sports competitions such as gymnastics, judges are influenced by subjective factors that may lead to unfair judgments. In future research, the integration of video-based body parameter measurement technology with human kinematic analysis and other related technologies can build an "electronic referee system" that automatically scores the movements of gymnasts, which can greatly reduce the influence of subjective factors in the scoring of sports competitions.

## 2. Current Status of Research

Motion and behavior analysis has a long history, and its research value is attractive to a variety of disciplines including psychology, biology, and computer science. From an engineering perspective, the field of behavior recognition has expanded to a wide range of high-impact social applications, not only in areas such as intelligent video surveillance, video retrieval, and human-computer interaction as previously mentioned but also in video-based behavior recognition which has also contributed greatly to retail analysis, user interface design, robot learning, medical diagnosis, and improving the quality of life of the elderly [7]. As a result, increased scholars are devoting themselves to the research in the field of behavior recognition. Nowadays, the mainstream behavior recognition research methods are roughly divided into traditional machine learning methods and deep learning methods, either of which is inseparable from the extraction of human behavior features from videos to characterize human behavior [8]. The current research development in the field of human behavior recognition is introduced from the perspective of the types of features used by various algorithms. Appearance shape features generally include size, profile contour, color, lightness, depth, etc. of moving objects, and these features are widely used in behavior recognition because they can better characterize human behavior details.

Taylor et al. were the first to use contours to describe human motion information. In the authors' approach, background subtraction is first used, and then, a series of background subtraction blocks are aggregated into a single static image. The authors propose two aggregation methods: the first method gives equal weight to all images in the sequence, resulting in a representation called the "motion energy image" (MEI) [9], which is used to indicate where motion has occurred, and the second method gives decaying weights to the images in the sequence, assigning higher weights to new frames and lower weights to old frames, which is called a "dynamic history image" (MHI), which is intended to be used to present the temporal order of motion [10]. Haghanikar proposed a motion history image-based interest point refinement algorithm to remove noisy interest points, extending the directional gradient histogram and optical flow histogram techniques from the spatial to the spatiotemporal domain to preserve temporal information [11]. H. Li and W. Li [12] addressed the problem that the representation of action recognition usually uses only shape features and ignores color features, inspired by the success of

color in image classification and target detection, and investigated the potential of color for behavior classification and detection in still images, experimentally showing that postfusion of color and shape information outperforms other methods for behavior recognition; the paper also gives that different color-shape fusion methods produce complementary information and combining them obtains advanced action classification performance. Moroz [13] proposed a background modeling method based on luminance invariant colors and adaptive Gaussian blending that can adaptively build and update shadows with color invariance assumptions for foreground target and background recognition in complex scenes, which achieves excellent recognition results without sacrificing real-time performance.

Based on the mechanical analysis of chaotic systems, Brandão investigated another Brandão system with energy cycles and bounds [14]. Recently, Reynolds et al. characterized the mechanics and energy of a brushless DC motor system with the help of the Kolmogorov system and Hamiltonian energy function and studied the physical background of the brushless DC motor system and its causes of chaos, which provides a good reference for other future mechanical analysis of chaotic systems with practical physical significance [15]. The accuracy of continuous gesture recognition relies heavily on two processes, action segmentation and semantic fitting, and continuous gesture recognition often has no clear segmentation points compared to speech recognition, thus giving birth to many machine learning-based methods to accomplish the definition of gesture segmentation points. Intuitively, the slowdown of gesture movement and the sudden shift of movement direction often represent the segmentation change points of gestures, and Chaudhry et al. defined the obvious gesture segmentation points based on this a priori condition through a plain Bayesian model [16]. In a later study, they further applied Bayesian networks based on the segmentation probability approach to segment continuous gestures into target gestures and transition gestures that separated target gestures which were classified by a two-layer CERF classifier and finally obtained good segmentation recall and recognition rates.

### 3. Chaotic System Equations for Human Action Recognition Analysis in Dancesport Video Images

**3.1. Chaotic System Equation Design.** Chaos refers to the unpredictable, random-like complex motion of a deterministic dynamical system that is sensitive to initial values. Due to the complex nature of chaos and the fact that scientists in different fields often have different understandings of chaos, there are many definitions of chaos from different perspectives, so that there is no unified and complete definition of chaos so far. A chaotic motion is a nonperiodic bounded dynamic motion, which is a random process that appears in a deterministic system. A chaotic motion is a nonperiodic bounded dynamic motion, which is a class of stochastic processes occurring in a deterministic system [17]. Chaotic systems are very sensitive to initial conditions, and small

differences in initial conditions can lead to very different results. This is known as “a mistake of a thousand miles.” The chaotic attractor is bounded, and its trajectory is always confined to a defined region, i.e., the domain of attraction. Chaotic motions are random and uncertain behaviors generated by a deterministic system, and this randomness is independent of external environmental factors and is generated spontaneously by the system.

$$\frac{d^q f(t)}{dt^q} = \frac{1}{\Gamma(n-q)} \frac{d^n}{dt^n} \int_a^t \frac{x(\tau)^2}{(t-\tau)^{q-n+1}} d\tau, \quad (1)$$

where  $n$  is an integer,  $q > 0$ , and there is  $1 < q < n$ .  $\Gamma$  denotes the Gamma function. The Laplace transform of equation (1) yields

$$L\left\{\frac{d^q f(t)}{dt^q}\right\} = S^q L\{f(t)\} + \sum_{k=0}^{n-1} s^k \left[ \frac{d^{q-1-k} f(t)}{dt^{q-1-k}} \right]_{t=1}. \quad (2)$$

When equation (2) is zero in the initial state, it can be simplified to obtain

$$L\left\{\frac{d^q f(t)}{dt^q}\right\} = S^q L\{f(t)\}. \quad (3)$$

The resulting transfer function of the fractional-order calculus in the frequency domain is given by

$$F(s) = \nabla \frac{1}{s^{2q}}. \quad (4)$$

When the motion state of a dynamical system is portrayed using the Lyapunov exponent, it is possible not only to calculate the rate of change of the system's trajectory points in the phase space but also to measure the long-term stability of the orbit of the chaotic system, which represents the overall quantity in time and space, rather than the local quantity. It can determine quantitatively the state in which the chaotic system is located. Consider a one-dimensional chaotic mapping with only one compression or stretching direction, while using the Lyapunov exponent definition of the one-dimensional mapping, one can determine the system motion orbit with the following expression:

$$LE = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=0}^n \ln |f'(x_i)|. \quad (5)$$

Here, equation (5) can only determine a Lyapunov exponent existing in three cases. When  $LE > 0$ , it means that in each local, the motion track of the system is in an unstable state, and the adjacent machine will chase to the present which means that the stable motion track of the double JA part will fold repeatedly, which can produce chaotic attractors; when  $LE < 0$ , it means that the motion track is a locally stable bolt, so it cannot form  $LE = 0$  which is the bifurcation point of the system when the LE stops and changes negatively, which means that the system transforms during the

chaos and multiplicity. Consider that the one-dimensional chaotic map has only one compression or extension direction, and the Lyapunov exponent definition of the one-dimensional map can determine the trajectory of the system. For a chaotic system, there must be several  $I$ -stop plying holes; therefore, by calculating the Lyapunov index that exists greater than zero, we can examine whether the system can generate chaos.

Self-similarity is one of the most important features of fractals, which is used to indicate that there is some similarity between the local and the whole itself. Since the structure of chaotic singular attractors is different from the usual geometry, there is self-similarity in this structure, and most singular attractors have fractional dimensions, so the geometric properties of chaotic systems can be studied by examining their spatial dimensions. And the fractal situation of the attractor is usually measured using the Lyapunov dimension defined as

$$D_L = k + \frac{2}{|\text{LE}_{k+1}|} \sum_{i=1}^{k-1} \text{LE}_i. \quad (6)$$

Here,  $k$  denotes the largest integer value that makes the  $\sum_{i=1}^{k-1} \text{LE}_i \geq 0$  condition hold, and for  $n$ -dimensional chaotic systems, in general,  $k = n - 1$ . By calculating the Lyapunov dimension, the state of the attractor in the  $n$ -dimensional phase space can be determined.

Continuous gesture motion contains rich node trajectory information, and without strong discriminative feature extraction methods to accurately capture the hidden motion patterns in the data, it is difficult for existing machine learning algorithms to obtain robust recognition systems from a limited amount of noisy training data. This part of the study will focus on how to dynamically model the time series generated by discrete observations of chaotic physical systems to provide the recognition system with a feature matrix reflecting the underlying kinematic properties. According to the dynamic reconstruction approach, it is first necessary to verify the stability of the dynamic gesture systems and their compliance with the conditions for the study of chaotic systems utilizing a symbolic spectrum approach and further to verify whether they are governed by fixed rules. According to the characteristics of chaotic systems, the trajectories of attractors with similar initial conditions will gradually separate over time, and chaotic dynamic systems with singular attractors will sensitively depend on the initial motion conditions, which will benefit the characteristic distribution of the system.

Based on the discrete nodal motion trajectory output from the convolutional gesture machine, a specific type of chaotic dynamical system is assumed to be used to simulate the gesture dynamic model, and then, a feature matrix composed of chaotic feature factors is established for classification recognition based on chaos theory analysis [18]. The discrete observation sequences of the gesture dynamic model are first verified by deterministic experiments whether they meet the conditions of chaotic time series analysis, and then, the spectral patterns between different gesture sequences are extracted by symbolic spectrum analysis for gesture segmentation. Chaotic feature factors such as correlation dimension, Lyapunov expo-

nent, and  $K$ -full are extracted from the phase space of the reconstructed time series, and then, the kinetic feature matrix describing the overall motion characteristics of the gesture is constructed. This avoids the difficulty of constructing and solving descriptive systems of motion equations and provides a new modeling idea for gesture feature engineering.

The assumption of a chaotic system based on a Gestalt motion model originates from the concept of a fixed point in the study of dynamics. In a simple single pendulum system, as shown in Figure 1, the fixed point is located at the lowest position of the pendulum. The important characteristics of the system motion are reflected in the region of motion around it. Regardless of the initial position of the pendulum, the system eventually converges to the fixed point, and the analysis of complex motion trajectories with noise can be reduced to the analysis of the fixed point. Overhead gesture motions also belong to dynamically dissipative systems, which are characterized by the convergence of the state-space volume to lower-dimensional manifolds over time. It is assumed that the continuous gesture is consistent with a nonlinear dynamical system, and in turn, a characteristic model based on chaotic dynamics can be developed to verify whether the hypothesis holds by experimental results.

The captured hand skeleton trajectories are expressed as discrete observation sequences of gesture motion trajectories. Unlike the handwritten letter recognition process, the overhead letter gesture trajectory in Figure 2 contains not only the letter shape itself but also the trajectory of transition motion, and these irregular motion trajectories make it difficult for the traditional algorithms based on image recognition to effectively capture the temporal and spatial features. The autocorrelation method is a sequence correlation method, which selects the delay time through the autocorrelation function, reduces the correlation between the reconstructed time series, and makes the dynamic characteristics of the sequence as little as possible. In addition, the time series in the actual system are discrete measurements of continuous data points, and the motion control equations of the system are usually unknown and complex, making it difficult to infer the motion features by data fitting. Incomplete state estimates and unintentional gesture movements often lead to nonlinearities in the observed sequence, and it can be assumed that the dynamic system fits a nonlinear Gaussian model. As opposed to inferring possible control equations, the model is fitted by finding the parameters that are most likely to explain those seemingly random samples. In chaos theory, chaotic attractors are mainly used to characterize nonlinear dynamical systems of order two or higher and apply to deterministic systems controlled by fixed rules.

To be done by decomposing the binary sequence into  $m$  disjoint subsets on the one hand and from the set  $\{1, 2, \dots, N - m\}$  for each of these subsets,  $m$  starting positions can be selected randomly. The reason the list of starting positions ends with  $N - m$  is that a subset of length  $m$  can be formed from the last possible starting position.

$$S_i = \begin{cases} 0, & x_i > M, \\ 1, & x_i \leq M. \end{cases} \quad (7)$$

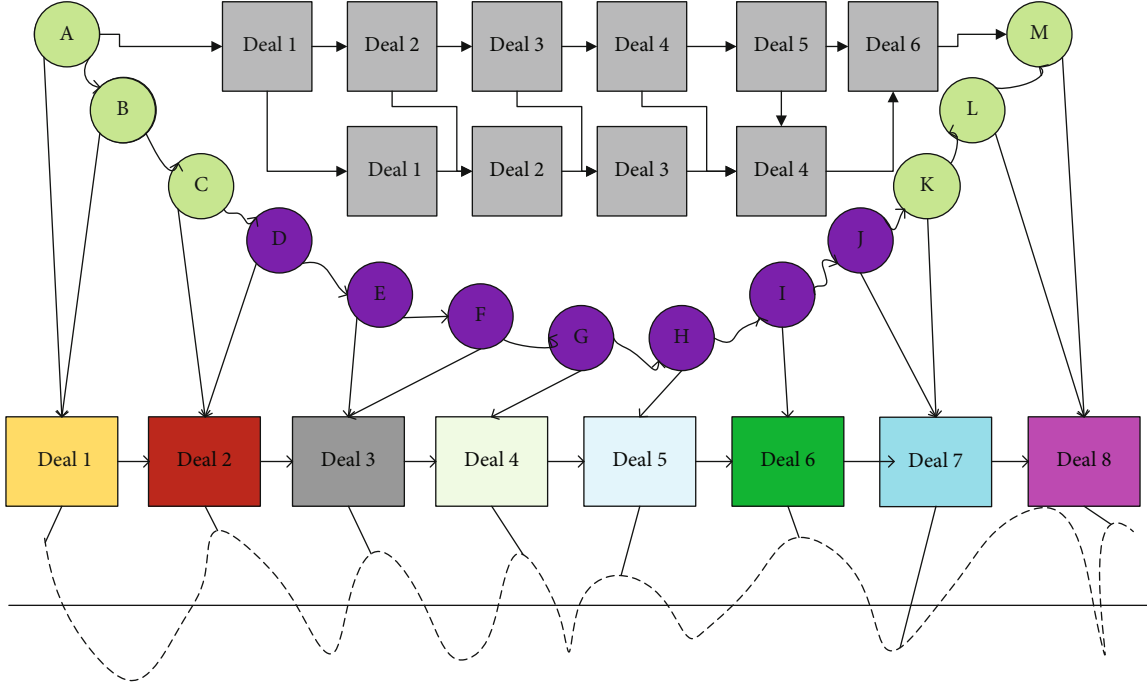


FIGURE 1: Motion trajectory of the overhead letter gesture.

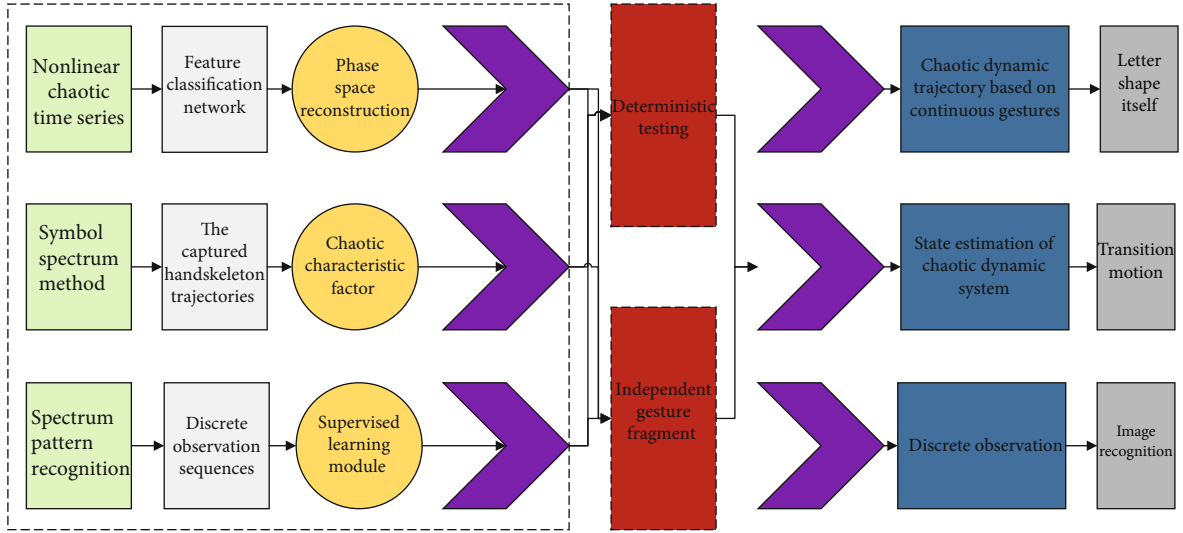


FIGURE 2: System algorithm framework.

And the corresponding characteristics are presented through numerical simulation to verify the analysis. The expression of the three-dimensional chaotic system is as follows.

$$\begin{cases} x = -ax - byz, \\ y = -cy - dxz, \\ z = kz - mxy. \end{cases} \quad (8)$$

is varied in a special range and the proper value is chosen, the system at this time can produce chaos.

$$D_L = 2 + \frac{K}{|LE_{k+1}|} \sum_{i=1}^{k-1} LE_k, \quad (9)$$

When different values of parameters are taken, the system will show different behavioral states. And when each parameter

$$\lambda_i = \lim_{t \rightarrow \infty} \frac{1}{t} \left( \frac{p_i(t)}{p_0(t)} \right), \quad (10)$$



$$\lambda_{\max} = \lim_{t \rightarrow \infty} \frac{m}{mt+1} \sum_{i=1}^n \ln \left( \frac{P_i(t)}{P_0(t)} \right). \quad (11)$$

Phase space reconstruction describes the state of mapping from one-dimensional signals to higher-dimensional signals and can avoid the mathematical solution of complex dynamical equations by capturing the underlying dynamical properties of discrete time series through dynamic modeling. The optimal embedding dimension is the smallest dimension that can satisfy the complete expansion of the chaotic motion. This requires constant calculation of the proportion of all neighbors occupied by false neighbors in the trajectory of the system during the process of increasing the dimension. Compared with the modeling methods based on descriptive variables, it can overcome the influencing factors such as noise, velocity variation, and individual motion amplitude differences and unify the dimensionality of the feature matrix without losing the dynamical features, while the seemingly complex and irregular one-dimensional time series signal has a feature distribution in the high-dimensional phase space sufficient to characterize the dynamical system. From the mathematical point of view of chaotic dynamics, the chaotic attractor is a set of values that represent the tendency of the system to evolve. The time series generated by the discretely observed chaotic physical system can be dynamically modeled to provide a characteristic matrix reflecting the potential kinematics of the recognition system. According to the properties of chaotic systems, the trajectories of attractors with similar initial conditions will slowly separate over time, and chaotic dynamical systems with singular attractors will depend sensitively on the initial motion conditions, which will favor the characteristic distribution of the system.

**3.2. Experimental Design of Human Movement Recognition from Dancesport Video Images.** The Lyapunov index quantifies the exponential rate of trajectory separation between moving attractors and describes how the trajectories on the attractors move as the system evolves, where the maximum Lyapunov index is used to measure the scatter index of nearby trajectories in the reconstructed phase space; the basic method of dynamic reconstruction is the delayed embedding method proposed by Takins, which reconstructs by delaying the coordinate state values equivalent to the phase space of the original space. Each row in the matrix represents a point in the high-dimensional phase space, and the delayed sequence of the original time series is recorded in a sliding time window of length  $m$ . The  $m$ -dimensional vectors are stacked to the matrix  $X$ , where  $m$  is denoted as the embedding dimension and  $t$  is denoted as the delay time.

$$X = \begin{pmatrix} x_0 & x_t & x_{2t} & \cdots & x_{xt-t} \\ x_1 & \cdots & \cdots & \cdots & \cdots \\ x_2 & \cdots & \cdots & \cdots & \cdots \\ x_3 & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{pmatrix}. \quad (12)$$

In a finite sequence with noise, the values of  $m$  and  $t$  directly affect the quality of the reconstructed phase space. The choice of the delay time determines the accuracy of the phase space structure: if  $t$  is too small, the chaotic attractor will be drawn along a straight line; if  $t$  is too large, the structure of the chaotic attractor will not be fully revealed. There are two main methods to predict the ideal delay time  $t$ : the serial correlation method and the mutual information method [19]. The autocorrelation method is a sequence correlation method, which reduces the correlation between reconstructed time series by choosing the delay time through the autocorrelation function so that the dynamical properties of the series are lost as little as possible. However, this method is essentially based on the concept of linearity and is suitable for judging linear correlations but not for nonlinear systems. And the mutual information method was proposed to find the first local minimum of the mutual information between the delayed time series  $\{m,\}$  and the original time series  $\{n,\}$  and determine the delay time effectively based on the feature that they share the least information. The recognition rate is about 93.68%, and about 1% of the samples cannot be applied to the phase space reconstruction method due to abnormal motion trajectory capture.

Assume that the dynamic gesture discrete observation of the system state  $\{w_1, w_2, \dots, w_m\}$  and the system state of delayed discrete observation  $\{q_1, q_2, \dots, q_m\}$  constitute the systems  $W$  and  $Q$ . According to information theory, one can obtain the information incited in the discrete measurement sequences of the respective systems, respectively:

$$H(W) = \lim_{n \rightarrow \infty} \sum_{i=1}^n P_W(W_i) \ln P_W(W_i), \quad (13)$$

$$H(Q) = \lim_{n \rightarrow \infty} \sum_{i=1}^n P_q(Q_i) \ln P_q(Q_i). \quad (14)$$

In  $I(t)$ ,  $P_{mn}$  denotes the joint probability that the instantaneous states between the two time series are the same.

$$I(t) = \lim_{m,n \rightarrow \infty} \sum_{i,j}^{m,n} P_{mn}(m_i, n_j) \ln \left[ \frac{P(m_i, n_j)(m_i, n_j)}{P(m_i)P(n_j)(m_i, n_j)} \right]. \quad (15)$$

Figure 3 shows the plotting of the mutual information function, and the  $x$ -coordinate corresponding to the first minimal value point represents the optimal delay time for reconstructing the phase space.

The quality of the phase space reconstruction and the extraction of chaotic features also depend on the proper embedding dimension  $m$ . When the motion trajectory in the high-dimensional phase space generates a projection on the one-dimensional spatial axis, the motion trajectory of the chaotic system is distorted and the projection is referred to as a chaotic time series in the geometric perspective. A spurious neighbor point is defined as a coordinate point in a higher-dimensional space where the projection distance of two nonadjacent points has a similar possibility on the

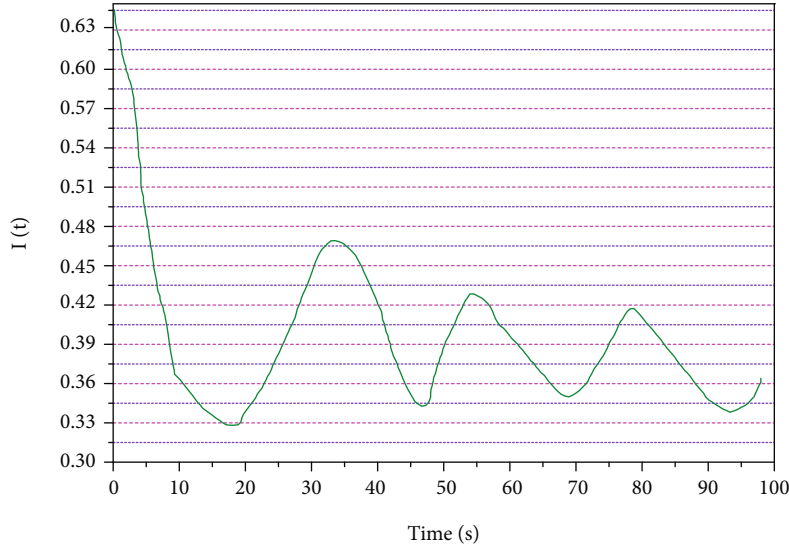


FIGURE 3: Plotting of the mutual information function  $I(t)$ .

one-dimensional spatial axis, and such a coordinate point usually brings about an irregular presentation of chaotic time series [20–22]. The basic principle of reconstructing the phase space is to unfold the geometric structure of the chaotic motion by increasing the value of  $m$ . First, through deterministic experiments, it is verified whether the discrete observation sequence of the gesture dynamic model meets the conditions of chaotic time sequence analysis, and then, the spectrum pattern between different gesture sequences is extracted by symbol spectrum analysis for gesture segmentation. In this process, false nearest neighbors will gradually appear, thus recovering the trajectory of its presentation in the one-dimensional time series distorted by chaos. The optimal embedding dimension is the minimum dimension that can satisfy the complete unfolding of the chaotic motion, which requires the constant calculation of the proportional relationship between all the nearest neighbors occupied by the false nearest neighbors in the trajectory of the system in the process of increasing the dimensionality. The complete unfolding of the internal structure of the chaotic motion needs to satisfy the condition of sieving out all the false nearest neighbors. For the time series obtained from discrete observations in practice, the initial condition is  $R = 30$  and  $m = 2$ , and the overall proportion of pseudonearest neighbor points is found. The optimal embedding dimension of the phase space is  $m$  when the value of  $m$  is increased until the overall proportion of pseudonearest neighbor points is less than 5% and stabilizes, and the geometric structure of the chaotic attractor has been fully recovered at this time. Figure 4 shows the 3D projection of multiple gesture trajectories in the phase space, and the gesture trajectories with different lengths and motion amplitudes are stably distributed in the high-dimensional phase space.

The correlation factor includes the correlation integral and the fractional dimension, which together determine the structure of the attractor metric, where the correlation

integral reflects the density of the number of state points in the radius domain denoted as

$$C(\varepsilon) = \frac{2}{N \times (N-1)} \sum_{i,j}^{m,n} HP_{mn}(m_i, n_j). \quad (16)$$

$x$  represents the state point on the attractor,  $H(x)$  is denoted as a Heaviside function, and  $\varepsilon$  is the value of the radius. A specific value of  $\varepsilon$  is set to obtain the corresponding correlation integral. Preexperiments were conducted with multiple gesture samples to observe the distribution of the samples at different radii, and finally,  $s = 50$  was set to make the most significant difference in the distribution. The fractional dimension describes the probability that any two points  $x(n)$  and  $x(k)$  on the attractor are separated by a distance  $r$  for some integer  $q$  denoted as

$$C(q, r) = r^{qD_q + D_q}. \quad (17)$$

Taking the logarithm of both sides together, the fractional dimension of the attractor can be obtained, which in turn defines the degrees of freedom required to describe the system.

$$D_q = \log C(\varepsilon) \log \varepsilon. \quad (18)$$

Lighting consistency in augmented reality systems is mainly concerned with the effect of lighting conditions in real scenes on virtual objects, including but not limited to the light and dark, reflected light, and shadows of virtual objects affected by the lighting conditions of real scenes, and the current research work on lighting consistency is mainly focused on real environment lighting parameter recovery techniques and virtual shadow generation techniques [23]. Temporal consistency in augmented reality is required for augmented

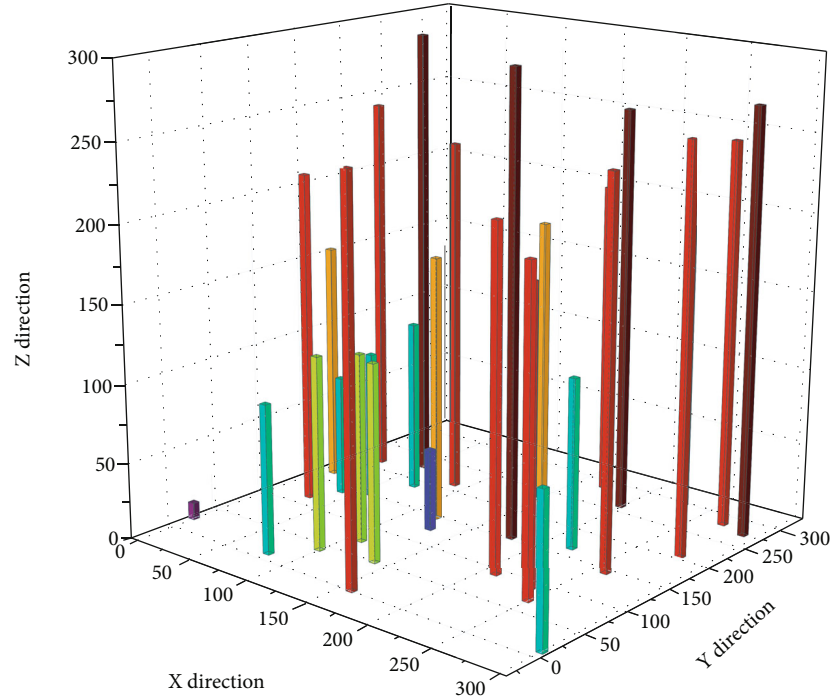


FIGURE 4: 3D projection after phase space reconstruction.

reality systems to enable real-time interaction. Among them, lighting consistency is based on the premise of geometric consistency and temporal consistency, because only when the geometric representation of the scene is recovered efficiently and in real time, the augmented reality system can perform accurate lighting recovery and obtain a strong sense of realistic reality fusion effect.

To better control the influence of these two factors on the spatial coordinates of the avatar model, this paper creates a new game object with the avatar model as a child game object and mounts the script to control the movement of the avatar model along the spline curve on the parent game object of the avatar model [24]. The script that controls the motion of the avatar model along the spline curve is mounted on the parent game object of the avatar model, and the animation state machine and the animation event callback script that is triggered when the dancesport animation develops to the end are mounted on the avatar model. All the feature descriptors extracted by the algorithm rely on the spatial-temporal bodies constructed around the trajectories of the feature points connected between frames, so the quality of the acquired trajectories directly affects the final recognition results. For the recognition task with human behavior as the main body, the trajectory information within the human body area contributes to the final recognition, while the trajectory information on the background relative to the human body is interference information, so we need to try to filter out this part of the useless trajectory.

## 4. Analysis of Results

*4.1. Chaotic System Identification Results.* The segmentation and recognition processes of consecutive gestures are com-

bined, and gesture frames with segmentation error less than 10% are optimized and considered not affecting the segmentation effect. Random combinations of three independent gestures are chosen to fully evaluate the performance of segmentation and recognition. The test dataset is partly from the experimental recruiter and partly from the combination of previous independent gesture segments, with 200 samples of each combination type. It was concluded from the experiments on independent gesture recognition that the random forest classifier was the best, so the random forest classifier was also used in continuous gesture recognition. Finally, the results are summarized in Figure 5, and the recognition rate is about 93.68%, and about 1% of the samples cannot be applied to the phase space reconstruction method due to the abnormal motion trajectory capture.

As shown in Figure 6, the movements of the overhead letter gestures are more complex and personalized than those of the stroke handwriting. The number of frames of letter gestures in the experiment is distributed between 100 and 200, and the spatial variation of the motion range is between 10% and ~30%, and their characteristic patterns are difficult to describe by descriptive metrics. In this case, the spectral analysis method has a stronger adaptive capability than the sliding window method. Unlike custom boundary conditions, motion segmentation would depend more on the potential motion properties of the segments of the feature fragments. The similar spectral shape in dynamic gestures proves that a deterministic rule does exist in this dynamical system to derive rich features. Instead of using deep learning algorithms to make approximate assumptions about model types, we obtain representations of chaotic dynamics from experimental data, which in turn are derived to produce feature vectors. We are not concerned with the local variation of



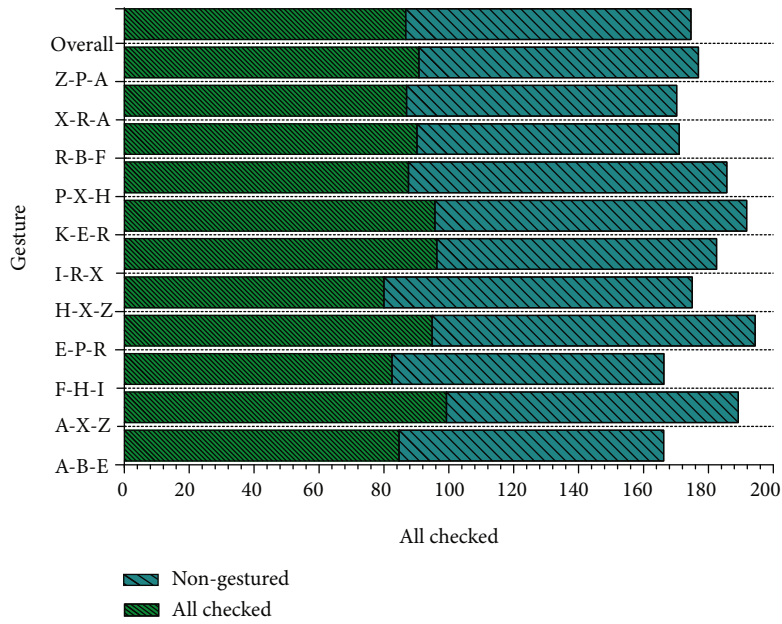


FIGURE 5: Recognition rate of consecutive letter gestures.

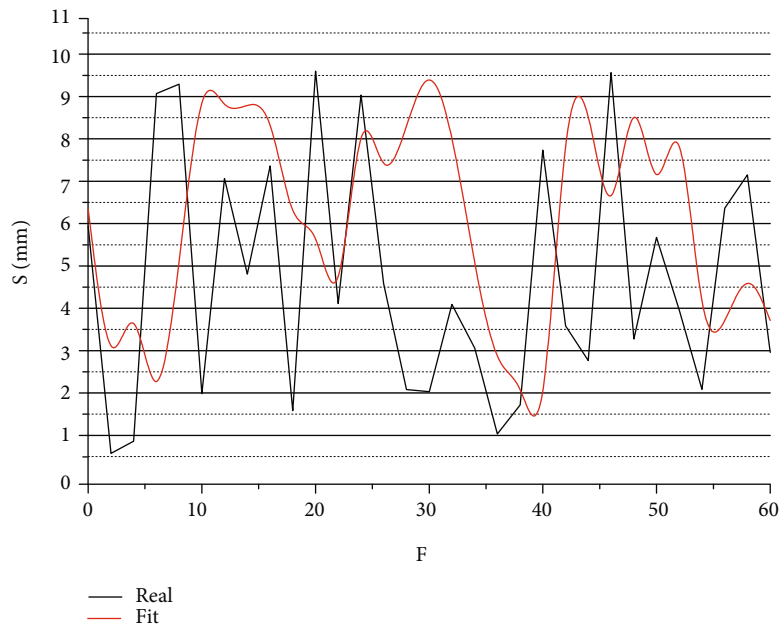


FIGURE 6: Simulation of spectrum-based gesture segmentation.

the time series but with the overall dynamical properties embedded and reflected in the phase space. Once the feature model proves to be effective in simple classifiers, it will further assist other learning algorithms for modeling spatiotemporal information. It should be emphasized that the performance of algorithms that perform both segmentation and recognition processes depends heavily on the development of the underlying dynamical properties, and the final recognition rate is not affected by the 10% bias in the segmentation process.

To compare the algorithmic performance of the chaotic feature matrix, the experiments compare the performance of 3D CNN with 3D convolutional deep learning features and geometric centroid-based descriptive features on raw data, respectively, as shown in Figure 6. Under the experimental conditions with certain arithmetic power and training samples, the chaotic feature matrix is generally better than the 3D convolutional neural network for gesture feature learning with a small sample volume. In the kinetic feature description perspective, the chaotic feature approach is

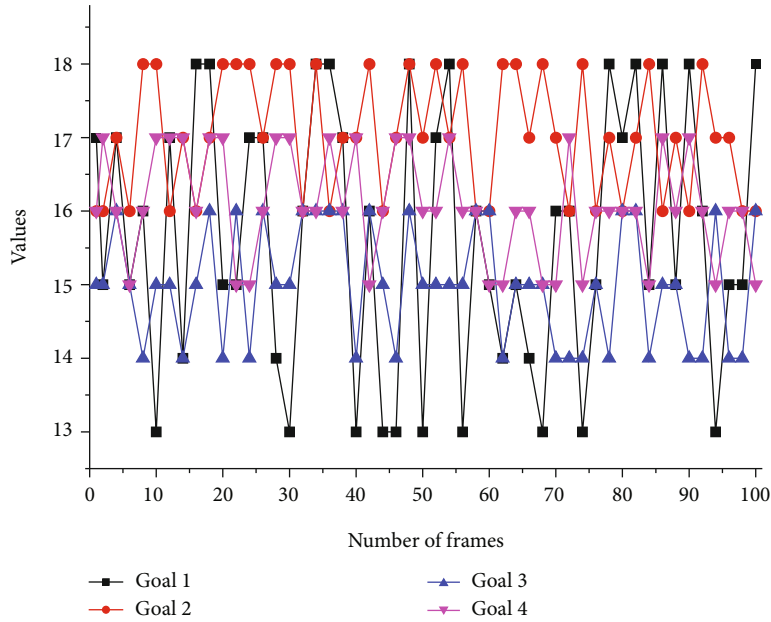


FIGURE 7: The first 100 frames of hand length measurement curve.

superior to the feature extraction methods with descriptive variables such as geometric centroids. To verify the fractional-order error system with the addition of a controller, a steady state can be effectively reached, thus enabling synchronous control of the fractional-order chaotic system. After the fractional-order error system is added to the fractional-order controller, the error system can converge to zero within a maximum of 40 s, which means that the fractional-order error system reaches a stable state in a finite time. Meanwhile, Figure 6 shows that the state variables of the drive and response systems are synchronized within 40 s, thus verifying the correctness and effectiveness of the designed fractional-order controller.

**4.2. Human Motion Recognition Results.** The focus of the two-arm spread width measurement is to locate the position of the left and right middle fingertip points at the horizontal limit position. The straight line where the leftmost and rightmost edges of the detection rectangle of the left and right palms are located is used as the straight line where the left and right middle fingertip points are located, and the horizontal coordinates of the leftmost and rightmost edges of the detection rectangle of the palms are subtracted to obtain the two-arm spread width. The measurement principle of two-elbow spread width is like that of two-arm spread width. The line where the leftmost and rightmost edges of the left and right fist detection rectangles are located is used as the line where the left and right elbow tips are located, and the horizontal coordinates of the leftmost and rightmost edges of the detection rectangles are subtracted to obtain the two-elbow spread width. The first 100 frames of the hand motion video are taken as the object of study, and the change curves of the hand length video measurements of target 1 and target 2 are shown in Figure 7. Since the hand motion of target 1 is more stable than that of target 2, the hand length measure-

ment of target 1 is also relatively more stable, and the measurement results are mainly distributed in the range of 16.0 cm~18.0 cm. Target 2's hand length measurement error is largely due to the large change in the size of the left and right palm detection frames due to the large wave of the hand, and the rectangular frame is often large and small in the initial 20 frames.

From the experiment, to obtain more accurate hand length measurement results in real time, one should try to keep the palm facing the lens and the hand to do the translational movement. In the case of rapid movement or rotation of the palm, the palm detection results are less accurate; at this time, the average value should be solved based on multiple measurements, to effectively reduce the hand length measurement error. It can be assumed that the dynamic system conforms to the nonlinear Gaussian model.

Figure 8 shows the real and measured extension lengths of the two experimental subjects, and the relative errors of the extension length measurements of targets 1 and 2 were 3.11% and 2.27%, respectively. Analyzing the sources of errors in the extension length measurement, we can see that the horizontal coordinates of the right shoulder peak point were considered to be the same as the horizontal coordinates of the center of the right-hand rectangular box, which were overcalculated about half of the arm width, resulting in an overestimation of the extension length measurement by 2-4 cm.

The human body and its joints are irregular geometries, and all kinds of human limb movements are variable speed curved movements in a three-dimensional space. Therefore, in the process of shooting a human motion video, errors such as shooting distance, angle, focal length, lens curvature, and scale inevitably occur, and there are also machine errors caused by camera shake and human errors introduced in the image processing process. Therefore, it is necessary to

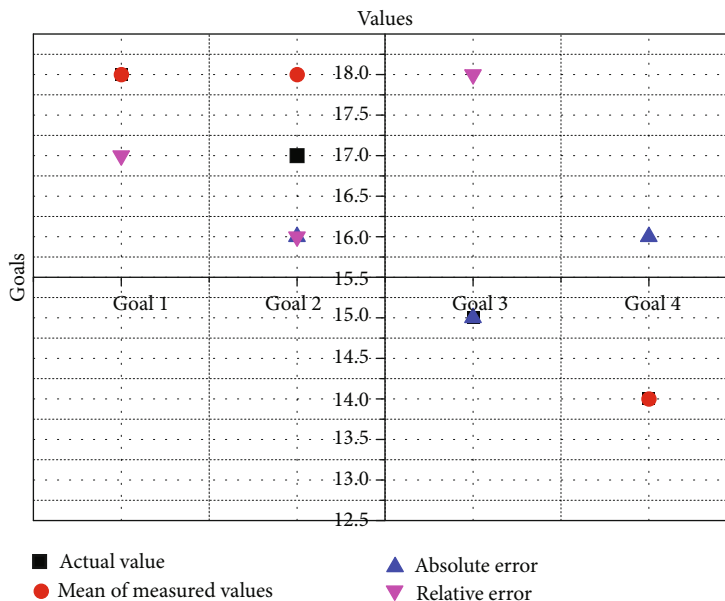


FIGURE 8: Error of actual and measured values of extension length.

conduct a detailed analysis of the sources of error in the video measurement of human parameters and take effective measures to control the sources of error and minimize the error in the measurement of human dimensions. Lens aberration is related to the type of camera lens, focal length and aperture settings, and other factors. Usually, the lens aberration is inversely proportional to the focal length. Therefore, in human parameter measurement experiments, digital cameras with medium and long focal length lenses should be selected for human motion video shooting as much as possible. In addition, the size of the aperture also affects the effect of aberration. In general, if the aperture of the aperture is smaller, the blurring and aberration of the image caused by spherical and coma aberration will be smaller.

### 5. Conclusion

In this paper, a framework for the study of nonlinear dynamics based on chaos theory is developed. Dynamic reconstruction can be defined as the identification of mappings, used to provide models for unknown multidimensional dynamical systems, hoping to find the appropriate mapping dimension of data points in the phase space to model the dynamics of a time series generated by a physical system with known chaos. The main motivation for dynamical reconstruction is to derive practical meaning from such a time series, thus bypassing the detailed mathematical knowledge needed to study the underlying dynamics. An important feature of the stability of nonlinear dynamical systems lies in the fact that it is characteristic of the whole system and explores some form of coordination between the individual parts. According to the dynamic reconstruction approach, we first need to verify whether the gesture interaction information is compatible with the conditions for constructing a nonlinear dynamical system and then to determine the system stability by studying the stability problem through the Lyapunov

direct method, which further verifies the deterministic state of the gesture motion system and proves the hypothesis that the gesture motion system with a multidegree-of-freedom structure can be analyzed by modeling chaotic dynamics. Finally, we concentrate on the behavior of nonlinear dynamical systems inscribed by fixed point attractors or singular attractors and seek suitable machine learning classification methods for the invariant features they possess.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The research was performed as part of the authors' employment under Jimei University.

### References

- [1] Y. Tian, X. Wang, Y. Geng, Z. Liuand, and L. Chen, "Inertial sensor-based human activity recognition via ensemble extreme learning machines optimized by quantum-behaved particle swarm," *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 2, pp. 1443–1453, 2020.
- [2] M. Heimerdinger and A. LaViers, "Modeling the interactions of context and style on affect in motion perception: stylized gaits across multiple environmental contexts," *International Journal of Social Robotics*, vol. 11, no. 3, pp. 495–513, 2019.
- [3] J. S. Lee and S. H. Lee, "Automatic path generation for group dance performance using a genetic algorithm," *Multimedia Tools and Applications*, vol. 78, no. 6, pp. 7517–7541, 2019.

- [4] A. Surana, "Koopman operator framework for time series modeling and analysis," *Journal of Nonlinear Science*, vol. 30, no. 5, pp. 1973–2006, 2020.
- [5] M. Bicher, S. Winkler, and A. Körner, "Modelling a Viennese ballroom: agent-based simulation to investigate complex behaviour," *Mathematical and Computer Modelling of Dynamical Systems*, vol. 26, no. 2, pp. 169–192, 2020.
- [6] M. R. Khokher, A. Bouzerdoum, and S. L. Phung, "A super descriptor tensor decomposition for dynamic scene recognition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 4, pp. 1063–1076, 2018.
- [7] W. Huang, L. Lin, T. Huang, J. Lin, and X. Zhang, "Scale-adaptive tracking based on perceptual hash and correlation filter," *Multimedia Tools and Applications*, vol. 78, no. 12, pp. 16011–16032, 2019.
- [8] X. Zhao and S. Ye, "Space reconstruction of audiovisual media based on artificial intelligence and virtual reality," *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 4, pp. 7285–7296, 2021.
- [9] A. Taylor, D. M. Chan, and L. D. Riek, "Robot-centric perception of human groups," *ACM Transactions on Human-Robot Interaction (THRI)*, vol. 9, no. 3, pp. 1–21, 2020.
- [10] D. Araújo, R. Hristovski, L. Seifert, J. Carvalho, and K. Davids, "Ecological cognition: expert decision-making behaviour in sport," *International Review of Sport and Exercise Psychology*, vol. 12, no. 1, pp. 1–25, 2019.
- [11] M. Haghanikar, "Visualizing dynamic systems: volumetric and holographic display," *Synthesis Lectures on Engineering, Science, and Technology*, vol. 3, no. 2, pp. i–87, 2021.
- [12] H. Li and W. Li, "Enhanced artificial bee colony algorithm and its application in multi-threshold image feature retrieval," *Multimedia Tools and Applications*, vol. 78, no. 7, pp. 8683–8698, 2019.
- [13] O. V. Moroz, "Model of self-organizing knowledge representation and organizational knowledge transformation," *American Journal of Artificial Intelligence*, vol. 4, no. 1, pp. 1–19, 2020.
- [14] M. Brandão, "Affirming versus relating: steps around, toward, and away from dance and performance art," *Dance Chronicle*, vol. 40, no. 3, pp. 353–373, 2017.
- [15] R. M. Reynolds, E. Novotny, J. Lee, D. Roth, and G. Bente, "Ambiguous bodies: the role of displayed arousal in emotion [mis]perception," *Journal of Nonverbal Behavior*, vol. 43, no. 4, pp. 529–548, 2019.
- [16] H. Chaudhry, M. S. Rahim, T. Saba, and A. Rehman, "Crowd detection and counting using a static and dynamic platform: state of the art," *International Journal of Computational Vision and Robotics*, vol. 9, no. 3, pp. 228–259, 2019.
- [17] A. Doostmohammadi, J. Ignés-Mullol, J. M. Yeomans, and F. Sagués, "Active nematics," *Nature Communications*, vol. 9, no. 1, pp. 1–13, 2018.
- [18] G. Zinman, "Nam June Paik's Etude 1 and the indeterminate origins of digital media art," *October*, vol. 164, pp. 3–28, 2018.
- [19] D. A. James and A. V. James, "Symmetry in European regional folk dress: a multidisciplinary analysis," *Leonardo*, vol. 53, no. 2, pp. 157–166, 2020.
- [20] S. Hong, J. Ryu, and H. S. Yang, "Not all frames are equal: aggregating salient features for dynamic texture classification," *Multidimensional Systems and Signal Processing*, vol. 29, no. 1, pp. 279–298, 2018.
- [21] Y. Wang, Z. Man, and M. Lu, "Prediction of energy-efficient production of coalbed methane based on chaotic time series and Bayes-least squares-support vector machine," *International Journal of Heat and Technology*, vol. 38, no. 4, pp. 933–940, 2020.
- [22] M. Sangiorgio and F. Dercole, "Robustness of LSTM neural networks for multi-step forecasting of chaotic time series," *Chaos Solitons & Fractals*, vol. 139, p. 110045, 2020.
- [23] F. Mechner, "A behavioral and biological analysis of aesthetics: implications for research and applications," *The Psychological Record*, vol. 68, no. 3, pp. 287–321, 2018.
- [24] M. Cooney and A. Sant'Anna, "Avoiding playfulness gone wrong: exploring multi-objective reaching motion generation in a social robot," *International Journal of Social Robotics*, vol. 9, no. 4, pp. 545–562, 2017.