

## *Retraction*

# **Retracted: IoT Networks Assisted Baduanjin Auxiliary Training System Based on Depth Camera**

### **Security and Communication Networks**

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*Security and Communication Networks* has retracted the article titled “IoT Networks Assisted Baduanjin Auxiliary Training System Based on Depth Camera” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the editorial board.

### **References**

- [1] P. Wan, Y. Liu, and H. Gao, “IoT Networks Assisted Baduanjin Auxiliary Training System Based on Depth Camera,” *Security and Communication Networks*, vol. 2022, Article ID 4429898, 7 pages, 2022.
- [2] L. Ferguson, “Advancing Research Integrity Collaboratively and with Vigour,” 2022, <https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/>.

## Research Article

# IoT Networks Assisted Baduanjin Auxiliary Training System Based on Depth Camera

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Baduanjin auxiliary training system has insufficient feature definition for similar actions, which affects the recognition accuracy of effective action data. A depth camera-based Baduanjin auxiliary training system is designed. The depth camera is used as the core to design the peripheral circuit and develop the relevant firmware in the hardware part. TPS2552 is used to design the USB current limiting protection circuit, and a CrossLink chip is used to realize the interface and level conversion. In the software part, the human body 3D model of Baduanjin training is generated and the parameters of the human body model are obtained by establishing the mapping relationship between the model and the human body features in the image. Based on the automatic calibration of Baduanjin motion feature points by the depth camera, the motion posture was analyzed and summarized, the attitude auxiliary indicators were established, and the posture standard was judged by comparing the distance of the posture joints in the reconstructed 3D human body model. The system test results show that the recognition accuracy of Baduanjin auxiliary training system based on the depth camera is 96.25% for effective action data, which is 11.53%, 15.28%, and 13.06% higher than that of Kinect, motion intervention, and behavior recognition auxiliary training system, respectively. Therefore, the system can provide analysis and guidance for Baduanjin movement.

## 1. Introduction

It has carried out various excavation and collation projects for traditional sports health preservation projects [1] based on the essence of traditional sports health preservation in order to adapt to current people's living habits and health demands. To begin with, four sets of traditional sports health preservation talents, namely, Baduanjin, Yijin Jing, the six-character formula, and Wuqinxi, have been promoted, resulting in a more systematic and scientific traditional sports health preservation project system [2]. This is not just an unavoidable need in the context of a "healthy China," but also a critical step in the preservation of traditional culture. Traditional sports health preservation, as an essential bearer of traditional culture, contains a rich spiritual diet and extremely scientific fitness approaches. One of the representatives is Baduanjin [3]. The physical health condition of

challenging groups may be successfully enhanced via long-term and systematic Baduanjin practise [4]. Its slow movement pattern and practise arena of achieving "union of body and mind" might help challenging groups better their health and psychological and spiritual levels [5]. In the traditional Baduanjin training, the training method based on naked eye observation is usually used. With the development of computer vision, people begin to use cameras to capture and analyze athletes' movements. In sports training, it is used to analyze and track the athletes' actions from the video image sequence, scientifically quantify and analyze the athletes' sports characteristics, and realize the analysis and comparison of athletes' posture. Then, using principles of human physiology and physics, this research proposes techniques for enhancing sports activities to aid training, thereby avoiding the situation in which conventional sports training is solely dependent on experience. At present, the

research on auxiliary training system has become a hot issue. Min and Mou used Kinect to obtain human body color video and depth data, calibrated multiple Kinect data using the least square method, and fused them using the Kalman filter algorithm [6]. Finally, the user's action sequence and standard sequence are scored according to the matching rules. Ren transmitted the 3D movement data of athletes to the computer through the built-in color video stream and depth data stream of Kinect, analyzed the motion characteristics, and provided targeted training plans for athletes [7]. Xu et al. promoted the exercise of cognitive function through the model mapping of mirror image and repeated detection to ensure the posture recognition rate [8]. Tian-Kui developed an auxiliary training system by analyzing each posture in the movement process by combining CNN with traditional image processing methods of corrosion and expansion [9]. The training process of Baduanjin can be recorded by using the auxiliary training system, and accurate modeling and calculation can analyze the training effect and give appropriate guidance and feedback. The original motion information obtained by using motion capture equipment is easier to record, save, and analyze in the future. The existing design of the auxiliary training system, on the other hand, is insufficient in defining the features of related actions. The benefits of cheap cost, excellent compactness, high efficiency, and strong anti-interference ability are commonly employed with depth cameras, which can collect all depth information by photographing the whole scene at once, considerably reducing picture acquisition time. As a result, this study proposed an auxiliary training system of Eight-dan Brocade based on the depth camera to intuitively assess and direct the movement of Baduanjin.

## 2. Hardware Design of IoT Networks Assisted Baduanjin Auxiliary Training System Based on Depth Camera

The hardware design of the system takes the depth camera as the core, designs the peripheral circuit around it, and develops the relevant firmware. The structure is shown in Figure 1.

The imaging circuit of the hardware of Baduanjin auxiliary training system mainly consists of TOF sensor, TFC controller, and its peripheral circuit. The TOF sensor sends a modulation pulse to the laser driver plate to drive the laser to emit a continuous modulation wave. After receiving the light pulse reflected back from the scene, the sensor imaging array uses  $n$ -phase step to integrate the charge generated by the reflected light. Then, the digital quantity obtained by the internal ADC sampling is sent to the TFC controller through the differential interface to complete the phase difference calculation. Finally, the phase difference data are uploaded to a PC for further analysis and processing through USB2.0. At the same time, the USB PHY chip can also receive configuration parameters from the upper computer to configure the working parameters of TOF camera. The image data transmission interface of sensor is LVDS interface. The LVDS interface is commonly used, and

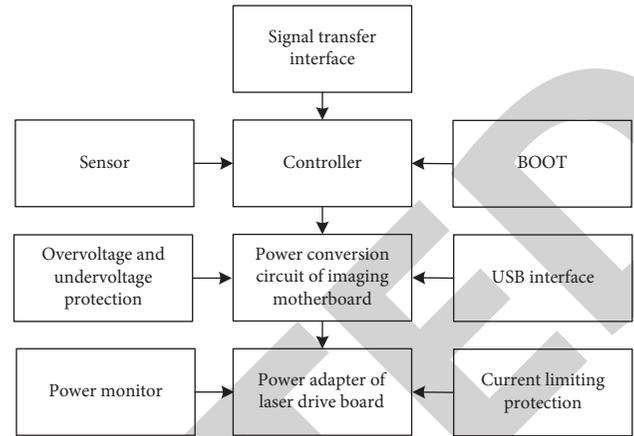


FIGURE 1: Overall structure of system hardware.

the IO level of most FPGA chips supports LVDS25 level, so LVDS differential clock and differential data output by image sensor can be directly connected with FPGA. In addition, during LVDS data transmission, a terminal resistor with a resistance value of 100 $\Omega$  needs to be matched at the receiving end, so you can either connect the terminal resistor on the hardware or enable the terminal resistor inside FPGA in the software program. When the load in the circuit is abnormal, the current in the circuit can reach several amperes, thus causing damage to the circuit. Therefore, it is necessary to design current limiting protection circuit to provide current limiting protection for input power supply and load when the access load overcurrent occurs, so that the circuit can work safely and reliably. TPS2552 is used to design the USB port current limiting protection circuit, as shown in Figure 2.

The TPS2552 chip provides a current limiting protection threshold ranging from 75 mA to 1.7 A. In this paper, the current limiting protection threshold of the USB port is set at 500 mA. The CrossLink family of FPGA chips contains one or two MIPI D-PHY cores and can also be used to implement MIPI D-PHY functionality through its internal logic resources. The chip supports MIPI DSI, MIPI CSI-2, SubLVDS, and other protocols or interfaces, and users can easily use it to achieve interface and level conversion functions. In this paper, the LIF-MD6000-80 chip is used to realize the interface parsing and interface conversion of MIPI CSI-2. Its internal resources are rich, which include 5936 LUTs, 1 GPLL, 2 MIPI D-PHY cores, and two on-chip oscillators (48 MHz and 1.0 kHz). The USB interface is very weak against electrostatic discharge, so it is necessary to use additional protection elements to prevent ESD interference to data transmission. TPD2EUSB30 supports up to USB3.0 standard and provides 4.5 V DC breakdown voltage. Low capacitance, low breakdown voltage, and low dynamic resistance make TPD2EUSB30 can achieve optimal static protection effect for high-speed differential IO. The Zynq7030 chip is selected as the main controller, and each Bank has its corresponding function. Bank0 is mainly used for instruction and configuration functions during system startup, and Bank112 is a dedicated high-speed transceiver

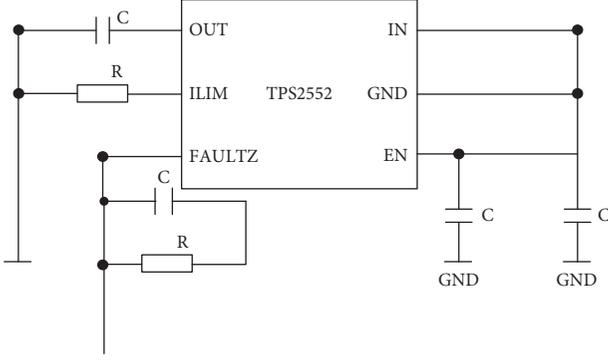


FIGURE 2: USB port current limiting protection circuit.

module. Most pins of Bank12, Bank13, Bank33, Bank34, and Bank35 can be used as a regular I/O port, which can be carried out on the pin according to the demand by the FPGA configuration. Bank500 and Bank501 are dedicated pins for MIO, and their functions can be flexibly configured according to requirements. Bank502 is dedicated to the communication between processor and dynamic memory. The JTAG interface of Zynq7030 is located in Bank0. Considering the current common JTAG debugger supply voltage is 3.3 V, the Bank0 supply pin is configured as 3.3 V and the CFGBVS pin is pulled up to 3.3 V through a resistance of 10 k $\Omega$ . PUDC\_B is pulled up to VCCO\_34 by a 1 k $\Omega$  resistor with jumper ground reserved.

### 3. Software Design of Baduanjin Auxiliary Training System Based on Depth Camera

**3.1. Generate 3D Model of Baduanjin Training.** The purpose of human pose estimation is to obtain the position and angle of each part of the human body in the image in two-dimensional plane or three-dimensional space. The Baduanjin auxiliary sports training system obtains the posture data of athletes and coaches through the human posture estimation algorithm and provides intuitive sports analysis guidance for training through quantitative analysis and comparison. The Baduanjin auxiliary training system's tracking procedure relies heavily on the model-based human posture estimate approach. First, the Baduanjin-trained three-dimensional human model is created. It shows a generative counter-measure network to recreate a 3D human model (GAN). Given a person's video, CNN extracts the spatial aspects of the picture for each frame image, Gru learns the temporal features of the video sequence, and regression predicts the SMPL parameters and SMPL model for each frame. The SMPL model is a simple linear human skin model that may describe various human bodies using parametric posture and posture.

There are 75 attitudinal parameters, including three degrees of freedom for each joint point and the global translation of the joint root point. SMPL specifies a standard model. The attitude parameters and posture parameters are supplied before fitting the attitude. The standard model is adapted to various postures based on the appropriate nonrigid deformation. First, the video is broken into frame

sequences by feeding the supplied frame sequence into the model, which outputs the associated posture and form parameters for each frame [10]. The double-layer node graph is calculated according to the predefined body node graph and the initial posture and attitude parameters. The marching cube algorithm is used to extract triangular meshes from the volume model and sample additional external nodes, which are used to calculate the nonrigid deformation of nonhuman parts. The time encoder is adopted because the future frame can obtain clues from the past video attitude information to evaluate the motion function [11]. After noise reduction, if a person's posture is fuzzy and ambiguous or the body is partially occluded in a given frame, the human motion posture information in the previous frame can help and restrict the subsequent posture estimation [12]. The loss of encoder consists of two-dimensional and three-dimensional pose and shape loss. The formula for calculating the total loss of Gru time series is as follows:

$$F = L_1 + L_2 + S. \quad (1)$$

In formula (1),  $F$  represents the total loss of time series,  $L_1$  and  $L_2$  represent 2D and 3D losses, and  $S$  indicates antagonistic loss. The calculation formula of two-dimensional and three-dimensional loss can be expressed as follows:

$$L = \sum_{a=1}^m \|b_a - b'_a\|. \quad (2)$$

In formula (2),  $b$  and  $b'$  represent input data and 3D joint position, respectively,  $a$  indicates serial number, and  $m$  represents the total time. Confrontational losses can be expressed as follows:

$$S = \|\chi_a - \chi'_a\| + \sum_{a=1}^m \|\gamma_a - \gamma'_a\|. \quad (3)$$

In formula (3),  $\chi$  and  $\gamma$  are attitude parameters and body parameters, respectively, and  $\chi'$  and  $\gamma'$  are the 3D joint values of the parameters. The frame sequence is initially sent to the convolutional neural network, and the feature generation function generates a feature vector for each frame. These are sent to a GRU layer. This layer generates potential feature vectors for each frame based on the previous frame. Then, the eigenvector is input to the regression element with iterative feedback in HMR. At the beginning, the incomplete outer surface makes it difficult to fit the model. It is necessary to continuously update the attitude and body parameters of the reference frame through the continuously fused surface.

**3.2. Automatic Calibration of Eight-Segment Motion Feature Points Based on Depth Camera.** A depth camera can be regarded as a visual distance sensor that can capture object contour and depth. The infrared laser generator emits the pulse light wave of a specific wavelength and receives it by the infrared camera. The depth image with distance information is formed through the signal processing of the photosensitive element. In three-dimensional space, due to the change of depth and the physical properties of the

camera itself, the formed depth map is a parallax map containing the original error offset [13]. The appropriate spots in the human body model and the fusion surface are searched for each pixel captured by the depth camera. The Euclidean distance is used to determine the joint point threshold. The fused surface is projected into two-dimensional space for the search of corresponding points between the depth map and the fused surface, and the corresponding points are found using the local search window. Search for corresponding points between the depth map and three-dimensional human body model [14]. First find the nearest volume node, and then search the nearest vertices around it. The corresponding points whose distance is greater than the threshold will be eliminated. This method can fully define the action characteristics of Baduanjin and identify similar actions. This method can achieve real-time processing on GPU without complex spatial data structure. For general camera models, multiple point coordinates will be involved in the imaging process, of which the two most important are two-dimensional image pixel coordinates and three-dimensional space point coordinates [15]. The depth parameter is one more dimension for the depth camera, and the general camera model is no longer applicable. Therefore, an original depth offset is introduced to form a projective spatial coordinate system. The projective spatial coordinates constructed by parallax map can be expressed as follows:

$$W = [p \ q \ \eta \ 1]^T. \quad (4)$$

In formula (4),  $W$  is the projective space coordinate,  $\eta$  represents the original depth offset, and  $p$  and  $q$  are 2D point coordinates. There is a conversion relationship between space and depth camera imaging points, and a pixel plane is defined in the physical imaging plane [16]. The definition of pixel plane has fixed rules. The relationship between the projective spatial coordinates of the depth camera and the European spatial point coordinates still conforms to the homography between image pairs [17]. Since the imaging principle of depth camera is still small hole imaging, the simplified form of depth camera model can also be expressed as follows:

$$rA_1 = \lambda [\omega_1 \ \omega_2] A_2. \quad (5)$$

In formula (5),  $r$  represents the scale factor,  $A_1$  and  $A_2$  represent homogeneous coordinates of 2D points and 3D points,  $\lambda$  represents the internal parameters of the depth camera,  $\omega_1$  is the rotation matrix, and  $\omega_2$  is the translation matrix. The homography between the feature pixels in the depth map and the feature points of the fixed object in space includes the internal parameter matrix and external parameter matrix of the depth camera [18]. The parameters of the internal parameter matrix are only related to the camera itself and will not change [19]. The homography matrix may be constructed by knowing the pixel coordinates and the midpoint coordinates in three-dimensional space, and the internal parameter matrix and external parameter matrix can be decomposed to provide the starting value of depth camera calibration [20]. Two types of characteristics are used to calibrate Baduanjin action feature points: skeleton motion

and nonrigid node deformation. The binding term is employed as a constraint in this article to guarantee that the motion generated by these two sets of factors is homogeneous. It should be noted that the binding term only constrains the nonjoint motion on the body node as a penalty term, while the nonrigid deformation of the external node is regularized by maintaining the motion similar to that of other nodes in the same graph structure [21]. In addition to geometric regularization, this paper also uses a statistical a priori to avoid unnatural human posture.

### 3.3. Design Human Posture Estimation Module.

Traditional sports training often relies on manual experience guidance and cannot accurately analyze key movements [22]. Human posture estimation is the most important part in the auxiliary training system. By obtaining human posture information from video or image sequence, the motion posture is analyzed and summarized and the posture auxiliary index is established. The human posture estimation module of the system is described in detail below. Different people have different heights and postures, and when performing the same action, everyone's action range is also different. Therefore, the attitude estimation module should have good universality in terms of feature definition of motion recognition algorithm, facing the bone structure of different populations [23]. For trainers in different positions and different heights, it will bring other differences to the data of joint points. In order to avoid the difference caused by people's height and distance from the camera, this paper uses 5 joint angles composed of 15 important joint points as the system index for auxiliary analysis. The five joint angles are recorded as angle 1 (head, neck, and chest), angle 2 (left shoulder, left elbow, and left wrist), angle 3 (right shoulder, right elbow, and right wrist), angle 4 (left hip, left knee, and left foot), and angle 5 (right hip, right knee, and right foot). The number of frames of start action and end action is obtained from the collected continuous action frames, and the continuous action is divided into short multistage actions with the start frame and end frame. For recognition, the whole segment of data is broken into small multisegment actions, which enhances accuracy and provides more feedback information. The joint point coordinates based on position coordinates are varied for various persons and in different places. The same action features are the same for various persons or different locations based on the angle characteristics. The changing trajectory of joint angle may be studied and led intuitively using a varying number of frames. The joint point distance of posture in the rebuilt three-dimensional manikin is used to determine if each motion is standard or not [24]. Specifically, Euclidean distance is used to calculate the distance of each joint point in standard motion video and test video. The distance formula is as follows:

$$H = \sqrt{(X_u - X_v)^2 + (Y_u - Y_v)^2 + (Z_u - Z_v)^2}. \quad (6)$$

In formula (6),  $H$  represents the trajectory distance of joint points,  $(X, Y, Z)$  is the coordinate, and  $u$  and  $v$

represent Baduanjin standard video and user test video. Through comparison, think of a threshold. In Baduanjin training, the lower the threshold, the more conventional the user's posture. In this research, the contour features recovered from target detection are further processed using a human posture estimate approach based on contour edge features and image processing technologies. The contour edge of the object is first determined using the Canny edge detection algorithm, and then the coordinates of human joint points are determined using image processing techniques such as horizontal scanning and human length proportion constraint. The human posture estimation process of Baduanjin auxiliary training system is shown in Figure 3.

In this paper, the training images of Baduanjin learners are used as the input and the similarity of joint angle trajectory comparison of master motion demonstration is used as the auxiliary training index. The process of the collector executing the eight-segment brocade action is continuous. When identifying, it is impossible to determine when to start and end. Only the whole segment of action data can be used as input to identify the overall continuous curve. There is a master exercise demonstration in the dataset. This demonstration video can be used as a teaching video for users to learn and reference in the early stage of the Baduanjin training model and as a sample of standard actions in the later stage. We stipulate that the demonstration video shall be used as the standard video of Baduanjin for reference and the user's training video shall be judged as the test video. Using the demonstration video as the standard video, we compare the Baduanjin training video of other users with the standard video. The higher the similarity, the more standardized the Baduanjin action is. If the similarity is poor, we think the action error needs to be adjusted. So far, the design of Baduanjin auxiliary training system based on a depth camera has been completed.

## 4. System Test

**4.1. Test Dataset and Running Environment.** There is no appropriate dataset for the Baduanjin auxiliary training system; thus, we used some Baduanjin films as the design system's dataset. We broke the whole Baduanjin into eight fundamental actions to allow comparison and judgement: two hands grasping the sky, left and right bow, single lift, rear glance, wagging head and tail, two hands ascending feet, saving fist, and standing on tiptoe. There is one normal video and ten test videos in each action. The depth camera acquisition equipment is approximately 3 m distant from the collector's execution posture and action location, and the depth camera is set horizontally on the experimental platform. There are no additional restrictions for participants' clothing color, laboratory lighting, or collecting setting backdrop throughout the collection procedure. There were 10 participants in the data collection, including 4 women and 6 men. The collectors performed the basic movements of Baduanjin 9 times, and a total of 720 Baduanjin movement samples were collected. Each motion data sample includes

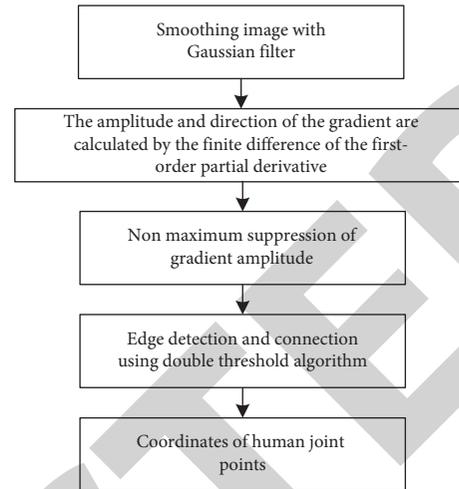


FIGURE 3: Human posture estimation process.

three types of pose data: color video and depth video in AVI format and bone spatial position information in TXT format. Each row is the 3D joint point spatial coordinates of 20 joint points in the same frame in the saved bone data. This system tests Ubuntu18.04 configuration in environment. The number of bits of the operating system is 64 bits. Python programming language is used to realize the algorithm model. TensorFlow, a deep learning framework, is used as the main framework. At the same time, Cuda10.0 was used for GPU acceleration operation. Because of the large number of datasets and long training time, this paper selects GPU for image feature extraction, which can improve the speed of operation and have high accuracy of output results.

**4.2. System Test Results and Analysis.** The system is tested on the established Baduanjin dataset. In order to test the effectiveness of the designed Baduanjin auxiliary training system based on a depth camera, the recognition accuracy of Baduanjin effective action data is taken as the evaluation index to measure the practicability of the designed system for Baduanjin auxiliary training. The auxiliary training systems based on Kinect, motion intervention, and behavior recognition in the literature are taken as the control group for the comparative test. The test results are shown in Table 1.

According to the system test and comparison results in Table 1, the recognition accuracy of Baduanjin auxiliary training system based on a depth camera for effective motion data is 96.25%, which is 11.53%, 15.28%, and 13.06% higher than that of Kinect, motion intervention, and behavior recognition. Therefore, the designed Baduanjin auxiliary training system can recognize and match the effective action data and is better than the existing auxiliary training system in recognition accuracy. The system has high reliability in judging whether the user's posture is standard or not, makes the user have a more intuitive understanding of the discrimination rules of Baduanjin basic action, and has certain practicability in guiding the user to learn Baduanjin action.

TABLE 1: Comparison results of the system test.

Basic action	Recognition accuracy of Baduanjin effective action data (%)			
	Baduanjin auxiliary training system based on depth camera	Baduanjin auxiliary training system based on Kinect	Baduanjin auxiliary training system based on sports intervention	Baduanjin auxiliary training system based on behavior recognition
Two hands holding the sky	93.33	86.67	77.78	83.33
Left and right bow	97.78	83.33	80.00	82.22
Single lift	96.67	85.56	82.22	78.89
Backward look	97.78	83.33	83.33	86.67
Wagging head and tail	95.56	84.44	78.89	85.56
Two handed climbing foot	94.44	86.67	85.56	83.33
Save fist style	96.67	83.33	81.11	84.44
Stand on tiptoe	97.78	84.44	78.89	81.11

## 5. Conclusion

An IoT-assisted Baduanjin auxiliary training system based on a depth camera is suggested in this study. The device has a high level of accuracy in determining whether or not the user's posture is normal. When the subject wears heavy clothing or interacts with external objects, the reconstruction effect is not always precise enough; tracking failure may also occur when the character moves quickly. The neural network approach is thought to incorporate semantic information to improve the reconstruction result.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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