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Analysis on smart seats intelligently correcting users' sitting posture

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Abstract. In contemporary times, an increasing number of individuals are encountering health-related issues stemming from extended periods of sitting, primarily attributable to improper sitting posture. Hence, the introduction of an intelligent seating solution into the market is imperative and holds significant potential for commercial success. Concerns regarding the health of children, namely their spinal development, as well as the need for sedentary workers to maintain a healthy sitting posture, have become significant issues for consumers. Currently, there are certain items in the market, such as backrests, which aim to partially correct sitting posture. However, these products have limitations in terms of requiring attachment or wearing, as well as lacking sufficient data support. Consequently, the user experience and scalability of these products are considerably inadequate. Based on the analysis of consumer big data by China Business News data (CBNData), there has been a notable surge in the market's appetite for premium corrective goods in recent years. There exists a market demand for products that are closely associated, specifically smart seats. Currently, researchers have conducted investigations on the recognition and reminder systems pertaining to sitting posture. This paper aims to conduct a comprehensive analysis and evaluation of the fundamental prerequisites and advancements in intelligent seating systems by employing literature analysis and review methods.

Keywords: Children's intelligent seats, sitting posture monitoring, sitting posture correction, spinal health

1. Introduction

Due to the advancement of social productivity and the progressive rise in academic demands, individuals in both professional and educational settings have universally experienced an increase in sedentary behavior. However, it appears that the majority of individuals tend to prioritize comfort over health concerns while engaging in prolonged periods of sitting. This inclination has resulted in several challenges, notably the increasing occurrence of cervical spondylosis among adolescents and individuals in their middle age. Based on the survey conducted in October 2021, the prevalence of suspected scoliosis in a specific district of Wuhan City was found to be 1.03%. Additionally, the survey revealed an overall incidence of aberrant posture at 13.20%. These findings suggest that the scoliosis rate in the school under investigation is not promising [1]. According to a study on scoliosis in children and adolescents, the univariate analysis reveals that 52.21% of this population exhibit improper seated positions [2]. In light of the aforementioned concerns and their associated health implications, it is imperative to promptly rectify improper and detrimental seating postures. In recent years, several

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existing gadgets designed to improve sitting posture have frequently neglected to consider individual variations, instead offering a standardized corrective approach to consumers via uniform equipment specs. However, the utilization of machine vision technology offers users the opportunity to access individualized and visually-based solutions for correcting sitting posture. This enables the corrective process to effectively cater to the unique needs and variations among individuals [3]. Nevertheless, the implementation of these remedial procedures has not been effectively integrated with tangible products, so failing to address the last stage of practical application.

This article aims to present a method of integrating current sitting posture monitoring technologies with chairs in order to create intelligent seating solutions. Initial deliberation is given to the utilization of several technological devices, including binocular cameras, pressure sensors, infrared cameras, and rangefinders, in the development of intelligent seating systems. This article examines the potential utilization of lightweight, tiny, and cost-effective binocular cameras, like to Microsoft's Kinect, in the development of intelligent seating systems. Furthermore, this essay will also investigate and evaluate the unconventional approaches of integrating alternative sensors with binocular cameras. The essay primarily use methodologies such as literature review, conceptual analysis, and practical application to comprehensively examine and address the research inquiries. The implementation and utilization of the intelligent seats discussed in this article would effectively address the existing market void for premium children's learning desks and intelligent seats. Consequently, this development would successfully contribute towards ameliorating the issues associated with suboptimal sitting posture in both adults and children.

2. The working principle of the main component of the binocular camera of the smart seat

The initial stage involves the conversion of the original image acquired by the instrument into a digital representation. In a previous study, Tang proposed an algorithmic approach to convert photographs into digital models [4]. To begin, it is recommended to employ a grid pattern for monocular calibration. Subsequently, stabilize the camera position and proceed to capture a series of twenty photographs of the pattern, ensuring variations in both positions and angles. Finally, proceed to meticulously measure and document the horizontal distance between consecutive corner points on the pattern. To establish a global coordinate system, the Z=0 plane is selected as the reference plane, with the pattern's plane serving this purpose. The origin of the coordinate system is defined as the top left corner of the pattern, while the Z-axis is determined by the vertical outward direction of the pattern. The world coordinates of all corner locations on the map are constructed simultaneously using the measured true distance. These coordinates are then stored in a list. Next, employing the Scale-Invariant Feature Transform (SIFI) technique, we identify and document the pixel coordinates of all corners present in the graph, storing this information in a distinct list.

This approach involves capturing a series of 20 photographs of the pattern depicted in Figure 1, each taken from various positions and angles. The coordinates of the points in both the real-world and pixel domains are recorded. Subsequently, the perspective projection model outlined in process (1) is employed to determine the internal and exterior parameters.

Figure 1. Specific images of the process of building a world coordinate system.

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$$Z_c \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} [r_1 r_2 t] \begin{bmatrix} X_w \\ Y_w \\ 1 \end{bmatrix} \tag{1}$$

Equation (1) describes the relationship between various parameters in the context of computer vision. In this equation, Zc denotes the scale factor, which quantifies the distance from the corner in the image to the imaging plane of the camera. The variables (u, v) represent the pixel coordinates of the corner, while (Xw, Yw, Zw) denote the corresponding world coordinates. Additionally, the right-hand side of equation (1) encompasses the camera's internal reference matrix and the external reference matrix associated with the relevant pattern. Given that we designate the plane of the pattern as $Z = 0$, it follows that the Z-coordinate for all corners is 0. The components r_1 and r_2 represent the first and second columns of the rotation matrix R. The homography matrix H can be expressed as the multiplication of the inner parameter matrix with the outside parameter matrix.

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} = \begin{bmatrix} f_x & o & u_0 \\ o & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} [r_1 r_2 t] \tag{2}$$

The DOF of the Homogeneous Transformations H is 8, let $h33 = 1$, and substitute it into equation (2)

$$\begin{cases} h_{31} uX_w + h_{32u} Y_w + u - h_{11} X_w - h_{12} Y_w - h_{13} = 0 \\ h_{31} vX_w + h_{32} vY_w + v - h_{21} X_w - h_{22} Y_w - h_{23} = 0 \end{cases} \tag{3}$$

The equation (3) has a total of 8 parameters whose values are currently unknown. In order to determine these parameters, it is necessary to obtain the pixel coordinates of four points as well as their corresponding world coordinates. By utilizing a linear path, we can then proceed to solve for the unknown parameters. By applying the orthogonality requirements of the r_1 and r_2 elements, we can derive the inner and outer parameter matrices for each graph. Once the parameter matrix mentioned above has been acquired, it is possible to establish the transformation relationship between world coordinates and pixel coordinates. The fundamental concept of picture stitching involves the projection of floating images onto a two-dimensional surface, specifically the target image. Hence, it is imperative to convert the pixel coordinates between two images. Consider a dual camera setup, where we denote the internal reference matrices of the left and right cameras as K_l and K_r, respectively. The external reference matrices are represented by E_l and E_r. Let Pw denote the world coordinates of a point on the pattern, specifically (Xw, Yw, Zw, 1). The projection points of this point on the imaging surface of the left and right cameras are denoted as P1 (ul, vl, 1) and P2 (ur, vr, 1), respectively. These relationships can be expressed mathematically as equation (4).

$$\begin{cases} p_l = K_l E_l P_w \\ p_r = K_r E_r P_w \end{cases} \tag{4}$$

E1= [rl1 rl2 tl], Er= [rr1 rr2 tr]. Then transform the Equation (4) ,the result is Equation (5)

$$p_l = K_l E_l Er^{-1} K_r^{-1} p_r \tag{5}$$

According to Mengfan Tang [2], a stable projection model has been successfully built at present.

The subsequent stage will involve the process of feature extraction. The initial stage of feature extraction involves the extraction of salient spots. The aforementioned contribution has facilitated the introduction of two widely used bone detecting point methodologies [5], namely Openpose [6], and Alphapose [7]. In light of the findings presented in reference [5], we have made the decision to propose an enhanced OpenPose approach. The conventional lattice model comprises numerous pivotal elements and exhibits a highly intricate structure [8], characterized by a substantial computing burden. To enhance computational efficiency, this study opted to exclusively employ a set of five pivotal data points. The anatomical regions in question include the left shoulder, right shoulder, neck, chest, and left eye. The diagram in question is depicted in Figure 2 below.

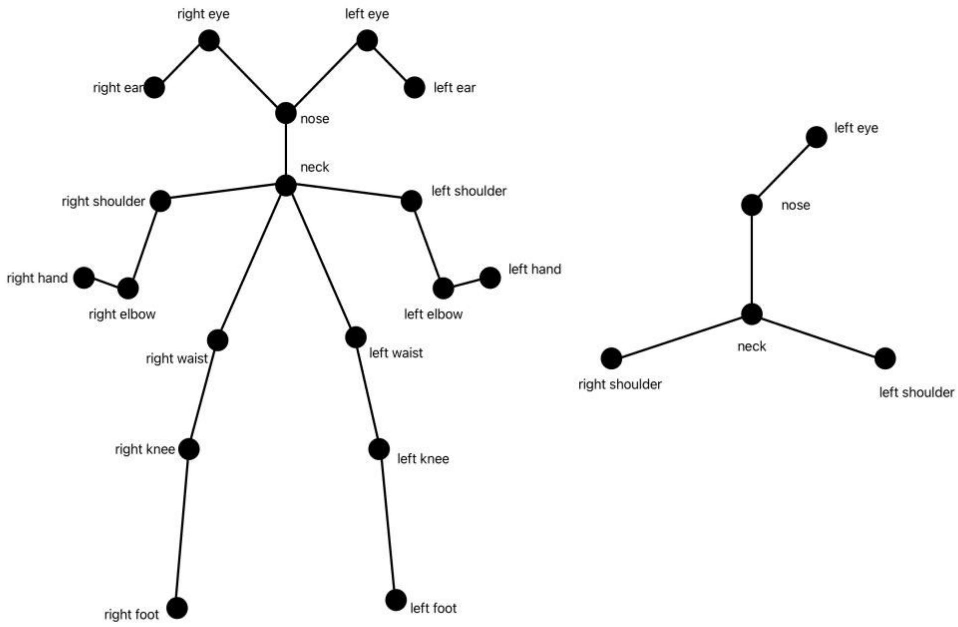

Figure 2. Key point collection and analysis diagram

The subsequent stage in the process of feature extraction involves the extraction of depth information pertaining to the identified important points. The primary SGM algorithm employs mutual information as a means to compute matching costs and involves intricate computational techniques. Hence, the utilization of the Census transformation-based method is prevalent in this particular computation [9]. The Census transform method computes the Hamming distance by using the relative grayscale relationship that exists between a given pixel and its adjacent pixels. To obtain precise estimates, we kindly request you to consult the reference provided as [10]. This section will provide a concise overview of the mind map (figure 3).

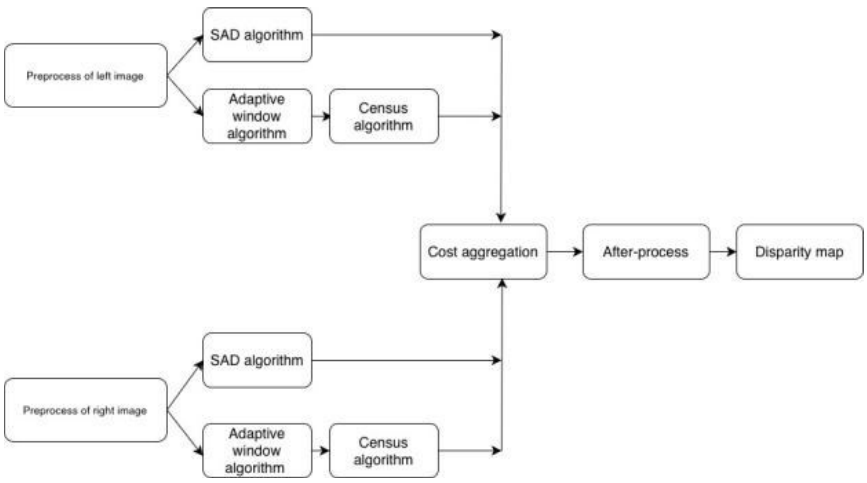

Figure 3. Calculating the Hamming distance mind map by transforming the relative grayscale relationship between pixels in the image and their neighboring pixels

The primary procedure of the adaptive window algorithm is the computation of the absolute grayscale difference for each pixel contained inside the window, followed by the calculation of their average value. Choose a specific pixel located within the boundary region of the image and designate it as the designated window. To determine the average of the absolute sum of grayscale differences for each pixel within a specified window, in order to adjust the edge area of the image to the window, a calculation is performed. Given the assumption that the left picture serves as the reference image, equation (6) presents the mathematical statement for calculating the average value of the adaptive window technique.

$$\mu(i,j) = \frac{\sum x \in W_x \sum y \in W_y \left|I_r(I+x, j+y) - I_r(i,j)\right|}{n} \tag{6}$$

Note: (i, j) is the position of the current pixel, n is the total number of pixels in the window, and I is the grayscale value of the pixel points.

$$\xi[I(p) \cdot I(q)] = \begin{cases} 0, I(p) \leq I(q) \\ 1, I(p) > I(q) \end{cases} \tag{7}$$

$$C_{cen}(x, y, d) = \text{Hamming}[c_s^L(x, y), C_s^R(x-d, y)] \tag{8}$$

Let $P = (x, y)$ be the midpoint pixel point within the left window. Let q represent a pixel point within the neighborhood of P. Furthermore, let $I(p)$ and $I(q)$ denote the grayscale values of the respective points connected by a bit, and let d represent the parallax value. To begin, it is necessary to compare the grayscale values of the central pixel with the grayscale values of its neighboring pixels using equation (7). Subsequently, the resulting Boolean values are combined according to equation (8) in order to derive the Gensus encoding string for point p. Next, determine the Census encoding string of point p in the right image, given a parallax value of d. The first matching cost of point p is determined by calculating the Hamming distance between the two encodings.

3. The working process of the the core components and the smart seat system

3.1. The working process of the the core components

One approach for incorporating pressure sensors into intelligent seating systems has been proposed in a scholarly publication [11]. The process diagram illustrating the conversion of pressure sensor data into sitting posture data is presented below (figure 4).

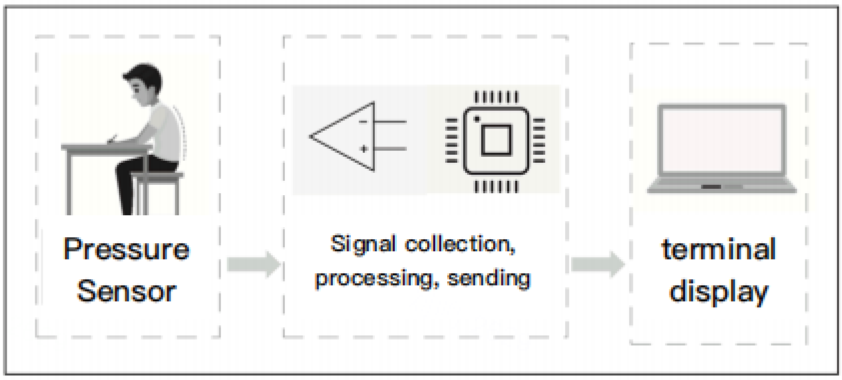

Figure 4. Flowchart for converting data collected by pressure sensors into sitting posture data.

As depicted in Figure 4, the precise configuration of sensors and hardware, including the central processing unit, has been documented [12]. The system is built upon the FSR pressure sensor and presents the organization and separation of the primary control core, sensor signal acquisition module, amplifier circuit module, and line transmission module, along with the design of the system program. For real-time analysis of how specific pressure is transformed into sitting posture [13].

3.2. The smart seat system

The aforementioned language describes the intelligent seat system discussed in this article, which encompasses pressure sensing devices integrated inside the seat area, dual recognition devices that rely on table arrangement, and a central processing system that is located within the seat. The hardware that is directly attached to each device will be connected using the 2.4 GHz Wi-Fi technology. The figure 5presented illustrates the intended installation of the intelligent seat system.

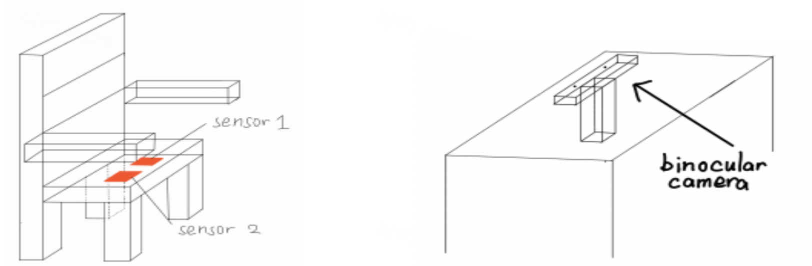

Figure 5. The installation intention of the smart seat system

4. Discussion

This paper provides a comprehensive overview of pertinent existing research, examines the various detection methods employed in identifying sitting posture through the utilization of dual cameras and pressure sensors, and presents a viable solution for an intelligent seat system. Subsequently, a more comprehensive examination of the merits and drawbacks of this undertaking will be conducted, building upon the aforementioned groundwork.

Indeed, the utilization of pressure sensors and dual cameras for the identification of sitting posture entails distinct merits and demerits for each approach. The pressure sensor offers the benefit of facilitating data conversion, while its primary drawback is the challenge of establishing standardized criteria for a healthy sitting posture within the database. On the other hand, the dual camera presents the advantage of effectively identifying incorrect sitting postures and establishing guidelines for optimal sitting positions. However, it encounters the difficulty of converting images into sitting posture data. The integration of these two ways enhances the accuracy of the system in detecting sitting posture and, to a certain degree, leverages the respective advantages of each method, effectively incorporating them into the design of the product. Hence, this particular scenario effectively addresses the issue pertaining to intelligent seat recognition for mobile sitting posture.

The primary challenge associated with the integration of technology into products lies in enhancing usability, minimizing expenses, and maximizing output. The detection of accurate sitting posture poses a significant technical barrier, and further challenges arise in determining the optimal location of various hardware components and establishing effective interconnections within this intricate system. Furthermore, the organization of whether the smart seat utilizes a wired and computer-based communication system for message transmission or only relies on personal reminders to the user is deficient. There exist numerous challenges that must be addressed in order to successfully implement mass production and operationalize the product.

5. Conclusion

Based on the preceding discourse, it can be inferred that there is a promising market outlook for mobile-based intelligent sitting posture monitoring devices. Nevertheless, prior studies have mostly concentrated on the selection between visual perception and tactile sensation, or have failed to integrate technological advancements with tangible consumer goods. The integration of optical and pressure sensors in the intelligent seat system offers a significant solution for the detection of high-end sitting postures. However, similar to every other commodity, there exist numerous practical manufacturing challenges that must be addressed before to commencing actual production. This study is subject to certain limitations, including the absence of an investigative approach and reliance solely on a preliminary analysis, hence lacking practical implementation. In subsequent periods, we shall address these deficiencies individually. With increasing emphasis being directed on intelligent seating and the emergence of proposed solutions for industrial challenges, there is a growing belief in the potential successful implementation of intelligent seat systems.

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