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SKELETON BASED HAND MISSING SCORE EVALUATION SYSTEM

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Abstract:

In this paper, a skeleton-based method is proposed for evaluating hand defects. Specifically, we take use of the existing hand skeleton extraction method and correct the extracted skeleton points, making them applicable for a hand with defects. Then, we combine the method above with the existing human hand defect evaluation system to automatically evaluate the concrete situation of the hand. The proposed method is tested on a dataset constructed by ourselves, which includes various cases where fingers and palm are missing. Experimental results illustrate that our method achieves excellent performance and can be applied to scenarios where the hand is partially missing with high accuracy. Our method can be helpful to forensic agencies in detecting and evaluating hand mutilations.

Keywords:

Hand defect; Hand skeleton; Defect assessment; MediaPipe

1. Introduction

Hand amputation refers to accidental severance of the hand as a result of a traumatic incident or intentional surgical removal of the hand due to severe disease or injury. The loss of a partial hand profoundly impacts an individual's capacity to perform routine tasks. The ability to carry out simple actions may become significantly challenging. This not only affects the person's physical capabilities but also their overall quality of life. Hand amputation requires immediate medical attention followed by long-term rehabilitation to regain as much hand function as possible.

To determine an appropriate treatment or rehabilitation strategy for individuals who have undergone a hand amputation, a scoring system [1] for missing hand assessments has been proposed. This scoring system aims to numerically represent the degree of disability experienced by individuals post-amputation. At present, the estimation of the missing hand score necessitates the involvement of a medical doctor. The doctor adheres to a specified standard, utilizing particular assessment instruments and guidelines. The process is comprehensive, examining the physical state of the patient's residual limb in detail. However, this evaluation procedure can be time-consuming and, may incorporate a degree of subjectivity.

This research introduces an automatic hand missing evaluation system based on hand skeleton. Existing hand skeleton methods may not be suitable for accurately capturing hand completeness, as they are primarily designed for healthy hands. To address this limitation, we propose an adjustment method that modifies hand key points extracted by Mediapipe [2] to accommodate defected hands, taking their contours into consideration. The hand missing score is then calculated based on established hand defect evaluation criteria [3]. Through experimental validation, we demonstrate the effectiveness and efficiency of our algorithm. This research contributes to automating the medical assessment of hand defects and fills existing research gaps in this field.

The rest of the paper is organized as follows. Section 2 presents the concepts related to this study, including hand skeleton extraction methods and hand function assessments. Section 3 proposes our method and explains its underlying concepts. The experimental results are presented and discussed in Section 4, and finally, Section 5 discuss the conclusion.

2. Related Work

2.1. Hand Modeling Methods

There are two main types of modeling methods for human hands. The first type involves creating a complete three-dimensional model of the hand [4]. These methods approach modeling as an optimization problem, aiming to make the model as similar to reality as possible. However, building a three-dimensional model requires estimating a large number of parameters, which can be time-consuming. In some applications, such as gesture identification, detailed information about each part of the hand may not be necessary. Another type of modeling methods [5, 6, 7] focuses on extracting key points of the hand, such as the palm, fingers [8], and fingertips [9], which represent the hand's skeleton. These methods use a simpler model, resulting in reduced time complexity. The key points provide sufficient information to capture gestures and track hand movement. To improve the accuracy of key point extraction, a perspective problem can be addressed by supplementing a single image with multi-view technology, known as Multiview Bootstrapping [10]. MediaPipe [2] is a framework that includes a palm detector and a hand landmark model. It has shown excellent performance in evaluating hand movement for patients with Parkinson's disease [11] and measuring joint angles [12].

2.2. Hand Function Assessment

It has been demonstrated that hand dexterity is closely correlated with the outcomes of Sequential Occupational Dexterity Assessment (SODA) [13], which measures hand-related disabilities in daily life. In clinical applications, Schoneveld et al. compiled 15 measurement tools [14] to assess the performance of patients. The study suggests that the selection of an appropriate tool should align with the specific measurement purpose. These assessments of hand function, in the form of scales or questionnaires, typically require manual measurements and must be completed by medical staff.

To reduce the need for manual involvement, sensor-based hand function assessments have been proposed [15]. These assessments commonly employ an instrumented glove to measure finger bending angles [16] and the range of joint motion [17]. Alternatively, computer vision-based hand motion detection [18] can also be utilized for evaluation. For instance, a multi-view video tracking recording system with a high-speed camera has been used to distinguish healthy and dysfunctional hand movements [19]. While gloved-based methods generally offer more accurate estimation compared to computer vision methods, their reliance on physical attachments can be burdensome and uncomfortable for the user.

3. Proposed Skeleton Based Hand Missing Score Evaluation System

This section presents a method for assessing the extent of hand impairment based on a hand skeleton. In the first phase (Section 3.1), we generate a hand skeleton for an impaired hand. To achieve this, we leverage the high-performance MediaPipe method. Subsequently, we refine the skeleton by eliminating the abnormal key points using our proposed hand contour and distance constraints. Finally, Section 3.2 calculates the hand impairment score based on the generated hand skeleton. The overall procedure is illustrated in Figure 1.

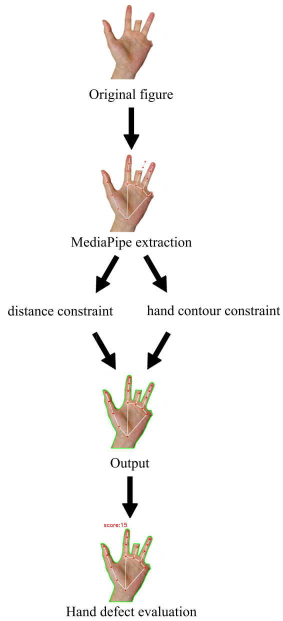

FIGURE 1. Procedure of our proposed method

3.1. Hand Skeleton Modeling Method for Impaired Hand

Due to its excellent performance, MediaPipe [2] is integrated as the initial model in our approach. We make the assumption that we have a clear image of the hand, where the palm is positioned flat on a plane and all fingers are fully extended. This ensures that there is no overlap in the hand outline, allowing for a more accurate analysis and assessment. MediaPipe extracts 21 key points from a healthy hand image to create a hand skeleton. However, when dealing with an impaired hand where certain parts are missing, certain key points may display abnormal behavior. Figure 2 visually depicts these abnormal key points, which can be categorized into two types: (1) key points located outside the hand contour, and (2) key points clustered closely together.

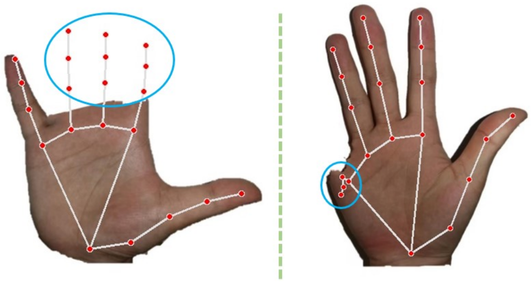

FIGURE 2. Two kinds of abnormal key points for an impaired hand

Figure 3 shows an example of a hand and its hand contour and key points. Libraries provided by OpenCV [20] is used to extract a hand contour. Figure3 shows an example of a hand and its hand contour and key points. Any key points located outside the hand contour will be removed. On the other hand, it is reasonable to assume that the distance between key points of a hand should exceed a certain range. Our method calculates the pairwise distance of all key points. A key point is removed if its distance to another point is less than a threshold. As a result, only necessary key points are remained to represent the skeleton of a impaired hand.

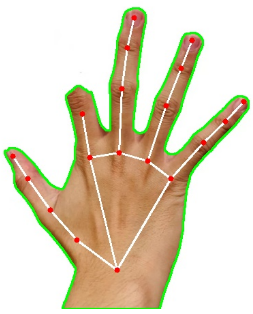

FIGURE 3. A hand and its key points extracted by MediaPipe and contour extracted by OpenCV

3.2. Automate hand defect evaluation method

To quantify the extent of hand impairment, the standard outlined in the Gradation of Disability caused by work-related injuries and occupational diseases [3] is used. This standard assigns a weight to each part of the hand based on its importance to hand functions, as illustrated in Figure 4. 45, 20, 15, 15 and 5 scores have been assigned to the thumb, first, second, third, and forth finger respectively according to their importance in daily duties. A higher score is assigned to a more seriously damaged finger. The final score is the summation of the score of each finger. A hand with a higher score indicates a more severe impairment of its functions.

Figure 5 show the 21 key points k_i, where $i = 0, 1, 2, ..20$, extracted from MediaPipe. It is worth noting that due to impairment, not all key points are present. $e(k_i) = 1$ indicates the i_{th} joint exists; otherwise, $e(k_i) = 0$. The average length of a finger section m is first calculated.

For the first, second, third and fourth fingers, we let $J_k = (j_1, j_2, j_3, j_4)$ denotes a tuple containing the joints from the palm to the tip, $S_k = (s_1, s_2, s_3)$ represents the values caused by a missing part from the palm to the tip, where k denotes the k^{th} finger. For example, $j_2 = (k_9, k_{10}, k_{11}, k_{12})$ are the joints for the middle finger, and its values being $s_2 = (20, 15, 5)$. $j_{1.5}$ and $j_{2.5}$ are calculated by extending the finger by the length $m/2$. We define a function $in(j)$ which returns 1 is the joint j is in the contour; otherwise, 0 is returned. For $k = 1, 2, 3, 4$, v_k is calculated by:

$$v_k = \begin{cases} s_1, & \text{if } in(j_{1.5}) = 0 \\ s_2, & \text{if } in(j_{1.5}) = 1 \text{ and } in(j_{2.5}) = 0 \\ s_3, & \text{if } in(j_{2.5}) = 1 \text{ and } e(j_4) = 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

As the thumb only contains two sections, $J_0 = (j_1, j_2, j_3)$ where $j_1 = k_2$, $j_2 = k_3$ and $j_3 = k_4$. $j_{1.5}$, $j_{2.5}$ and $j_{2.75}$ are calculated extending j_1 by the length $m/2$, and j_2 by the length $m/2$ and $3m/4$ respectively. As a result, v_0 is defined as:

$$v_0 = \begin{cases} 45, & \text{if } in(j_{1.5}) = 0 \\ 25, & \text{if } in(j_{1.5}) = 1 \text{ and } in(j_{2.5}) = 0 \\ 15, & \text{if } in(j_{2.5}) = 1 \text{ and } in(j_{2.75}) = 0 \\ 5, & \text{if } in(j_{2.75}) = 1 \text{ and } e(j_3) = 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Finally, the value V is calculated by summing the values of all figures, *i.e.*, $V = v_0 + v_1 + v_2 + v_3 + v_4$.

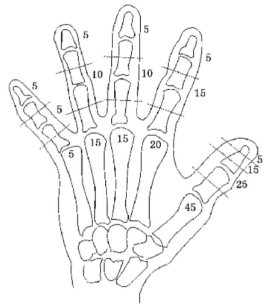

FIGURE 4. The standard for identify work ability-gradation of disability caused by work-related injuries and occupational diseases

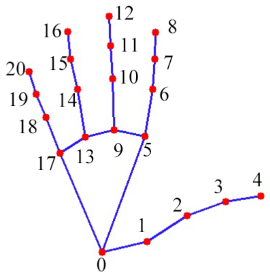

FIGURE 5. The key points and their indexes on a hand.

4. Experiment

Two-step evaluation of our model is carried out. The first experiment focuses on assessing the accuracy of the hand key point refinement, while the second experiment evaluates the precision of the hand missing evaluation. Our experiments are performed on a personal computer running Windows 11, equipped with an AMD Ryzen 5 4600H CPU, 16 GB of RAM, and an NVIDIA GeForce GTX 1650 GPU. For our experiments, we utilize Python 3.7.12, OpenCV 4.7.0.72, and Mediapipe 0.9.0.

4.1. Dataset

103 images are collected by our research team. 84 and 19 are collected from male and female subjects, and all individuals in the dataset fall within the age range of 18 to 22. We initially gather healthy hand images that meet the specified criteria, which include having the palm placed flat on a plane and all fingers fully extended. Impaired hand images with different missing levels are then created by randomly removing portions of a hand by using Meitu, an image editing software.

4.2. Result and Discussion

The correction of the hand missing score estimation has been made for 73 out of 103 images, resulting in an accuracy of 70.87%. To further evaluate the accuracy of the estimated values, the mean absolute error (MAE) was calculated. The MAE for missing scores is 3.72 for all images, while for the incorrectly estimated images, it is 12.76. Additionally, the average decision time, including key point and contour extraction, is 0.08 seconds. This indicates that our method has low time complexity.

Figure 6 presents selected results. The first three figures demonstrate favorable results, where the hand skeletons are accurately captured and the scores are calculated correctly. This can be attributed to the absence of a finger section, making identification easier. However, Figure (d) shows that our method struggles to determine the absence of the thumb due to the inaccurate location of key point k_2. Figure (e) exhibits a problem with skeleton extraction, as key point k_{18} is wrongly identified. Although the estimated value is correct in Figure (f), the key points of the first and fourth fingers are located incorrectly. These results indicate that our method performs well overall, but there is room for improvement in the skeleton estimation method.

5. Conclusion

The objective of this study is to introduce an automated evaluation system for assessing hand missing scores, thereby reducing the manual workload of medical professionals. We propose a key point filtering method that eliminates abnormal key points generated by MediaPipe[2], a deep convolutional network-based hand skeleton generation model, to account for missing parts in impaired hands. Subsequently, the hand missing score for the impaired hand's skeleton is quantified based on the standard for identifying work ability - Gradation of disability caused by work-related injuries and occupational diseases. Experimental results demonstrate that our method achieves a reasonable level of accuracy and efficiency. This study addresses a gap in key point extraction for impaired hands and offers support for rehabilitation efforts. Our method relies on an existing key point extraction technique that is primarily designed for healthy hands. However, this approach may be influenced by the presence of missing hand parts. To enhance the accuracy of our system, it is crucial to explore an extraction method specifically tailored for impaired hands. Nonetheless, one of the challenges we encountered is the scarcity of training samples for impaired hands. In future work, we plan to

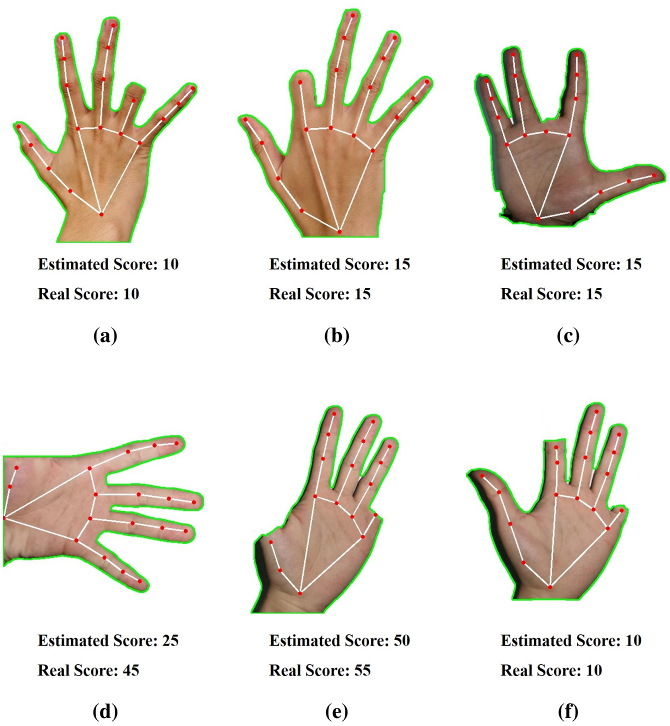

FIGURE 6. Examples of hand images, their real and estimated scores.

investigate the potential of transfer learning methods to assist in training our model and overcome this limitation.

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