iVoiding: A Thermal-Image based Artificial Intelligence Dynamic Voiding Detection System

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***Abstract*— This paper proposes a thermal-image based artificial intelligence dynamic voiding detection system, designated as iVoiding. iVoiding is composed of a thermal camera, AI recognition platform, and management platform. Furthermore, iVoiding uses deep learning technology to recognize human urination position and dynamically measure the spraying distances and angles of urine flows in the thermal images. The experimental results show that iVoiding provides an objective urine flow measurement that can really be achieved for the purpose of assessing the severity of lower urinary tract symptoms.**

Keywords—Voiding, Thermal, Lower urinary tract symptoms, Deep Learning

I. Introduction

Lower urinary tract symptoms (LUTS), the combinations of serial bothersome symptoms during voiding, is extremely prevalent in men, with rate as high as 62% at any age [1]. This prevalence increases consistently with age, reaching 80.7% in men over 60 years old [2]. In clinical, the severity of LUTS was evaluated by international prostate symptom score (IPSS). There are 7 items in the IPSS questionnaires, including incomplete empty, urinary frequency, intermittency, urgency, weak stream, abdominal straining and nocturia [3], which serves as the first-line tool to allow urologists to better understand the condition of patients' voiding. In the IPSS, we let patients determine how severity their urinary symptoms are in the past month. However, due to the fact that most patients suffered from LUTS are elder, recent studies have shown 30–70% of men could not complete the IPSS because they found the questions too difficult to understand [3]. There are 7 questions in IPSS with the challenges owing to problems with literacy, cognitive ability, visual acuity of the patients and increased time to perform this scoring. It's also hard for elder patients to remember what the voiding pattern really is in the past month, which leads to a recall bias. Visual analogue uroflowmetry (VAUS) score (Fig. 1) was then developed with the advantage of its simple score and easy understanding [4]. Although compared to IPSS, VAUS is more convenient and takes less time to be performed, it is still a subjective questionnaire based on patients' perception of bothersome symptoms and exist a recall bias, especially in older patients who have difficulties with memory. In addition, due to the original limitation of questionnaires, both IPSS and VAUS may not be 100% consistent with the patients voiding. Therefore, an objective tool to timely evaluate the LUTS is necessary.

To address this issue, we consider the need to automatically observe urination status. This paper proposes a novel voiding detection system, designated as iVoiding, which adopts thermal imaging and deep learning technologies. The stream data of voiding can be dynamically measured, and the severity of urinary symptoms can further be objectively assessed according to the measured results.

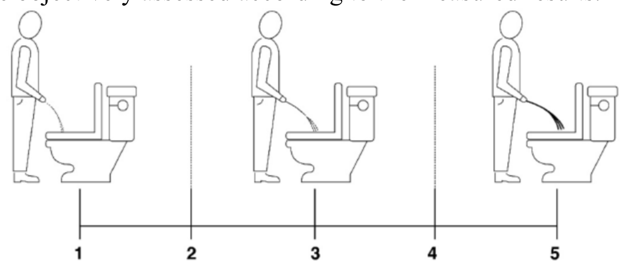

Fig. 1. Visual analogue uroflowmetry score(VAUS). A score with one being slowest stream and least volume, and five being fastest stream and large volume.

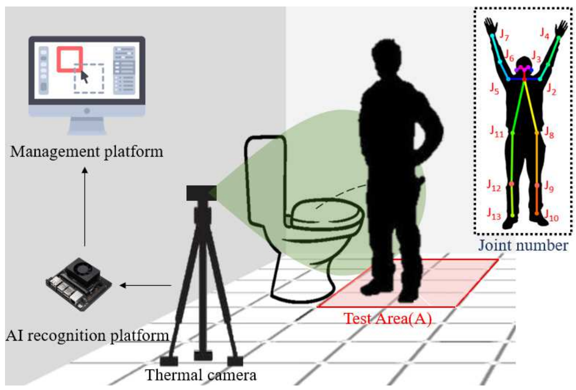

Fig. 2. System architecture of the iVoiding.

II. System Architecture

Fig. 2 shows the proposed iVoiding system architecture, which is composed of a thermal camera, AI recognition platform, and management platform. As shown, the iVoiding system captures thermal images in Test Area(A) by the thermal camera, and then coverts the human body shapes in the thermal images into 2D human limbs plane coordinates by using the proposed Thermal-Pose module in the AI recognition platform. The 2D human limbs plane coordinates are a set of 18-keypoint (denoted as J_i with 2D coordinates (X_i, Y_i) $(i \in \{0,1,\ldots,17\})$) and 17-edge human backbone coordinates data structure for each body shape. To alleviate shooting angle bias caused by various human height, this

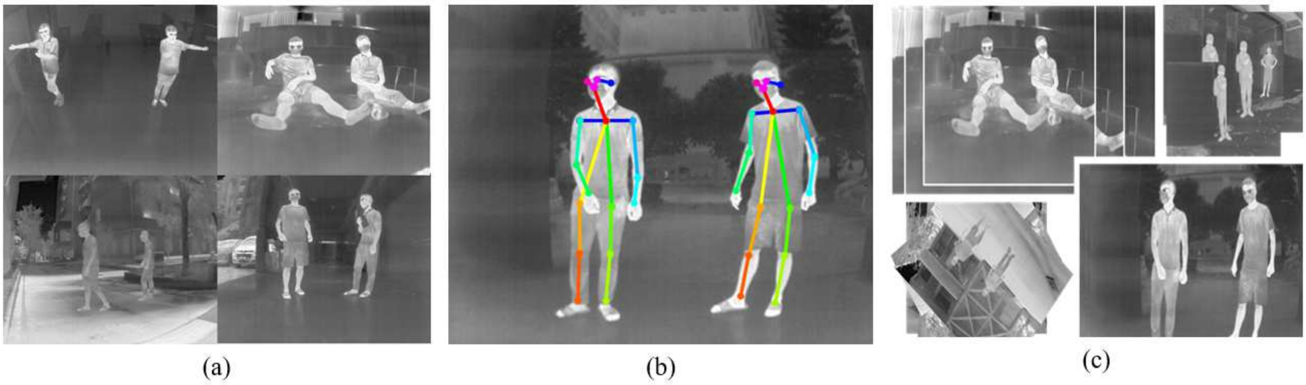

Fig. 3. Thermal-Pose module design. (a) the original dataset ; (b) A total of 18 keypoints with 17 edges annotated in each thermal imaging body pose instance ; (c)the approaches (i.e., scaling, cropping, rotating) applied for data augmentation.

paper considers the coordinates of keypoint J_8 (regarded as the position of left hip) as the reference point of urination position for adjusting vertical height of the thermal camera. Accordingly, the proposed Urine Flow Measurement Algorithm (UFMA) in the AI recognition platform is used to identify the position of voiding and measure the spraying distances and angle of the voiding flow in each thermal image.

A. *Design of Thermal-Pose Module*

The goal of the proposed Thermal-Pose module is to detect 2D human pose of people in the captured thermal images. To implement this module, this paper constructs an original dataset consisting of 12K thermal imaging body pose instances (as in Fig. 3(a)). (Note that the reason for utilizing the thermal images as the training dataset is to achieve thermal imaging-based human pose detection without privacy concerns on the use of RGB images) Each thermal imaging body pose instance in the original dataset is labeled with a total of 18 keypoints (i.e., nose, eyes, ears, neck, shoulders, elbows, wrists, hips, knees, and ankles) according to the body annotations in the COCO keypoint dataset [5] (as in Fig. 3(b)). Furthermore, data augmentation is applied to increase the original dataset size by a factor of 4. This is done by randomly cropping, scaling, and rotating approaches (as in Fig. 3(c)). As a result, the augmented dataset consists of 48K thermal imaging body pose instances annotated with 216K keypoints. The Thermal-Pose module is then built by means of the deep learning-based human pose detection technology (i.e., OpenPose model [6]) trained on the augmented dataset. Consequently, the Thermal-Pose module can monitor the thermal imaging scene of the Test Area(A), in which each detected person will be localized as the 2D human limbs plane coordinates (i.e., 18-keypoint and 17-edge human backbone coordinates data structure).

B. *Urine Flow Measurement Algorithm (UFMA)*

In the proposed UFMA scheme, the urination position is determined in accordance with the 2D human limbs plane coordinates in a thermal image. As shown in Fig. 4, the coordinates of the urination position **S** are calculated by combining the x-axis coordinate of the keypoint left wrist (i.e., J_4) and the y-axis coordinate of the keypoint left hip (i.e., J_8) into the 2D coordinates **S**(X_S=X_4, Y_S=Y_8). Furthermore, consider a point **R** represents the destination where the urine

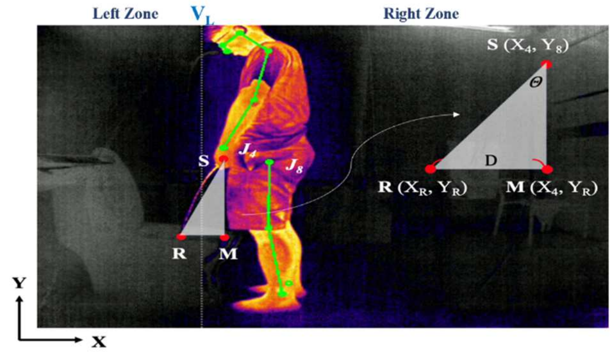

Fig. 4. The parameters denoted in the UFMA scheme.

flow sprays into the toilet. The coordinates of the point **R** (denoted as **R**(X_R, Y_R)) can be estimated by observing the location to the left with a higher temperature in the thermal image. Moreover, a point **M** with the coordinates **M**(X_M=X_4, Y_M=Y_R) can be established by means of the coordinates of **S** and **R**. By adopting the location information of points **S**, **R** and **M**, the UFMA algorithm is capable of estimating the spraying distance D of the urine flow (i.e., the distance between **R**(X_R, Y_R) and **M**(X_M, Y_M)) in accordance with the distance formula, i.e.,

$$D = \overline{RM} = \sqrt{|(X_R - X_M)|^2 + |(Y_R - Y_M)|^2} \quad (1)$$

The distance between **S**(X_S, Y_S) and **R**(X_R, Y_R)), denoted as $\overline{SR}$, can be computed by means of the same distance formula, i.e.,

$$\overline{SR} = \sqrt{|(X_S - X_R)|^2 + |(Y_S - Y_R)|^2} \quad (2)$$

As a result, the UFMA algorithm can obtain the angle Θ of urine flow (i.e., the included angle ∠MSR) by means of the inverse sine function taking the ratio of $D/\overline{SR}$, i.e.,

$$\Theta = sin^{-1}\frac{D}{\overline{SR}} \quad (3)$$

C. *Management Platform*

After obtaining the distance D and angle Θ in a thermal image by the UFMA approach at a time t, the AI recognition

Fig. 5. The deployment of the proposed iVoiding system in a toilet.

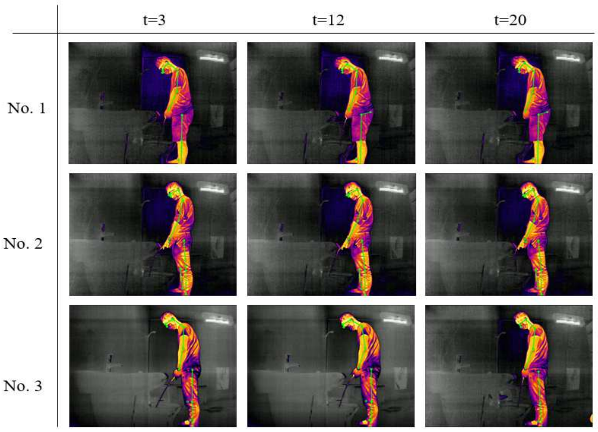

Fig. 6. The thermal snapshots taken from 3 volunteers for the urination test.

platform immediately transmits both D and Θ with the time t toward the management platform. The mangement platform records the received distance D, angle Θ, and time t in a database, and therefore is capable of providing timely and comprehensive information of urine flows (e.g., a result of spraying distance and angle changes in time). This information can be further analyzed to obtain a novel basis for assessing the severity of urinary symptoms.

III. Experimental Results

As shown in Fig. 5, the proposed iVoiding system was deployed in a toilet for performance evaluation. To reflect the practical performance of iVoiding, 3 healthy young male volunteers (denoted as No. 1, No. 2, and No. 3) who have been asked to drink water until they felt the urge to urinate were arranged for the experiment. Fig. 6 shows the thermal images of the urination of each volunteer taken at 3rd, 12th, and 20th seconds. It can be seen that the changes of distance and angle of the voiding stream from each volunteer can be observed in the thermal snapshots. Figs. 7 and 8 illustrate the spraying angle and distance measurement performance of the UFMA approach under different amounts of urine. It is observed that irrespective of the amount of urine being voided, during normal urination, the urine streams remain at a certain spraying angle for a while and the stream spraying angles are getting smaller at the ending period of the urination. Furthermore, the normal urine flows continue to spray for a certain distance for a period of time, while the spraying distances are shortened at the ending phase of the voiding.

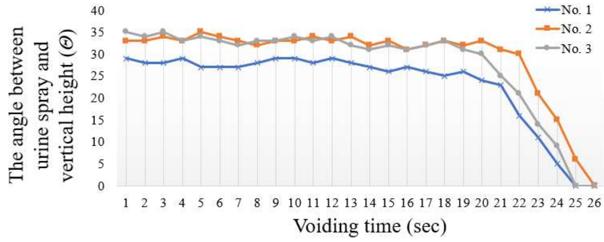

Fig. 7. Spraying distance, Θ, relative to voiding time, t.

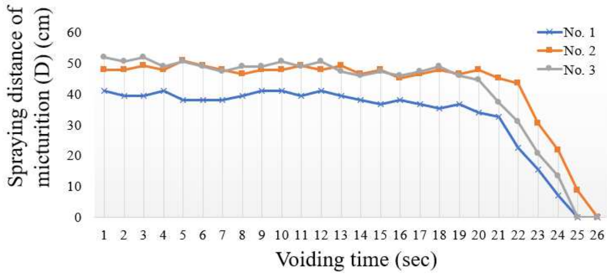

Fig. 8. Spraying distance, D, relative to voiding time, t.

IV. Conclusion and Future Works

In this paper, a thermal-image based artificial intelligence dynamic voiding detection system has been proposed, called iVoiding, which can be applied to evaluate the severity of LUTS. The iVoiding can improve the current assessment tools (i.e., IPSS and VAUS questionnaires) by providing an objectively and timely way for observing the urination of patients. The proposed iVoiding system has been implemented to track urination pose by a Thermal-Pose module, which can detect and covert human body shapes into the 2D human limbs plane coordinates in the thermal images. By using the information of 2D human limbs plane coordinates, the iVoiding system can detect urination position and measure the spraying distance and angle of urine flows by a UFMA scheme. Since the iVoiding tracks urination status based on thermal-imaging technology, it can be deployed in a toilet for medical observation without privacy concerns.

For future work, we will cooperate with the urology department at the tertiary referral hospital to apply iVoiding in healthy controls and patients to find out each cut-off value affecting the severity of LUTS.

References

[1] Irwin DE, *et al.*, "Population-based survey of urinary incontinence, overactive bladder, and other lower urinary tract symptoms in five countries: results of the EPIC study," *Eur Urol*, pp. 1306-1314, 2006

[2] Thorpe A, *et al.*, "Benign prostatic hyperplasia," *Lancet*, pp. 1359–1367, 2003.

[3] N Rodrigues Netto Jr, *et al.*, "Latin American study on patient acceptance of the International Prostate Symptom Score (IPSS) in the evaluation of symptomatic benign prostatic hyperplasia," *Urology*, pp. 46-49, 1997.

[4] Tiwari R, *et al.*, "Prospective validation of a novel visual analogue uroflowmetry score (VAUS) in 1000 men with lower urinary tract symptoms (LUTS)," *World J Urol*, pp.1267-1273, 2020.

[5] COCO-dataset keypoint evaluation Available at URL: https://cocodataset.org/#keypoints-eval.

[6] Z. Cao, *et al.*, "OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, pp. 172-186, 2021.