Real-Time Neonatal Body Length Estimation Based on an RGB-D Camera

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Abstract

Preterm newborns have extremely fragile skin and require care in temperature and humidity-controlled incubators, making physical contact during routine clinical procedures undesirable. Nevertheless, daily growth monitoring is essential for early diagnosis and assessment of neonatal development. Body length is a critical indicator of growth in preterm newborns; however, conventional manual measurement methods are often inaccurate, time-consuming, and may cause discomfort due to repeated handling. This paper presents a digital-based system for real-time preterm body length estimation designed to minimize physical contact while doing measurement. The proposed approach utilizes an RGB-D camera setup combined with 3D image processing and machine learning techniques. YOLOv8 is employed to detect key joint regions of the newborn's body from captured images. The distances between detected joints are then computed and used as input features for a machine learning model to estimate overall body length. Experimental results demonstrate that the proposed system can provide real-time body length estimation in practical clinical scenarios, offering improved efficiency compared to traditional measurement methods.

1 Introduction

Preterm infants' skin is extraordinarily delicate. Their skins are so thin and fragile that even the lightest touch to their skin can cause redness or tearing. To minimize stress and environmental factors during their clinical development stage, these newborns are cared for in temperature-humidity-controlled incubators that shield them from drafts, bright light, and loud noise until they are mature enough to tolerate disturbances in the external environment. Procedures are clustered so the infant can rest undisturbed in the same environmental conditions. The NICU (Neonatal Intensive Care Unit) room remains dimly lit with minimal noise to stabilize heart rate, breathing, and sleep. Soft bedding and gentle positioning ensure the baby's body lies naturally without overextension, while strict hand hygiene and minimal handling protect the skin. By combining these careful environmental and handling protocols, medical providers support the infants' daily development and obtain development measurement processes without compromising the safety of these vulnerable newborns [1,2].

Continuous monitoring of vital signs and growth parameters, particularly head circumference and body length allows medical providers to detect the earliest signs of stress or infection to the newborns. Traditionally, these measurements are performed manually using a soft measuring tape [3]. This method is inexpensive and easy to use, but it requires direct contact with the newborn's delicate skin. As a result, medical providers must proceed with extreme caution, and the process is both time-consuming and prone to measurement error [4].

Digital measurement techniques can overcome these limitations. By using cameras, medical providers can obtain a more efficient measurement compared to the traditional methods. Automated data capture also speeds up workflow, minimizing inter-observer variability for real-time growth tracking and decision support. In the long term, such technologies promise to improve NICU outcomes by ensuring precise, and timely assessments, while maintaining the highest standards of neonatal care.

Digital body measurement methods have also included 2D image-based approaches, depth-based sensing, and 3D reconstruction techniques [5,6,7]. In such systems, image processing methods such as segmentation, contour extraction, silhouette analysis, and geometric distance calculation have been applied to estimate body dimensions. More recently, machine learning and deep learning approaches, including keypoint detection and regression models, have been introduced to improve measurement robustness under varying infant postures and imaging conditions [8].

Despite recent advances in digital health technologies, the application of stereo-vision-based measurement systems in neonatal intensive care environments remains limited, particularly for body length assessment in preterm infants. Existing stereo-based approaches often require specialized hardware, complex setup procedures, and precise camera calibration, which make them challenging to deploy in real-world clinical settings [9,10]. In addition, calibration processes must be repeated whenever the camera configuration changes, further limiting their practicality for routine use within incubator environments. As a result, these systems are often not optimized for real-time clinical operation or seamless integration into neonatal intensive care unit (NICU) workflows. Therefore, there is a clear need for a practical, low-cost, and easily deployable measurement solution that can operate reliably using standard imaging. The proposed RGB-D camera-based system addresses this gap by leveraging a single-camera setup combined with machine-learning-driven estimation to enable real-time, non-contact body length measurement. By eliminating the need for stereo calibration and additional hardware, the system significantly reduces deployment complexity and operational burden. We have developed a head circumference measurement using a digital measurement system and reliable results are obtained [11]. Unlike our previous work in reference [11], which focused on neonatal head circumference measurement, the present study addresses body length estimation, requiring a different anatomical target, body keypoint configuration, and regression framework.

In our system, a RGB-D camera-based length-measurement system for the NICU combines a state-of-the-art pose estimator with a machine-learning regression model for real-time applications. The camera captures each newborn's image; the pose estimator then identifies joint locations, and the trained algorithm computes body length from those 3D keypoint coordinates. Results are displayed in real time on a monitor, allowing medical providers to verify measurements immediately. To validate the measurement accuracy, a dataset of 435 images is collected from the NICU and these data are divided into training (75%) and testing (25%) data. Adaboost algorithm is used to estimate the body length. The estimated results are compared with the manual measurement system. By eliminating contact with the newborn skin, this approach minimizes stress and the risk of skin injury, accelerates workflow, and improves consistency across different operators.

2. Measurement System

Figure 1 shows the overall configuration of the proposed neonatal body-length measurement system [11], including the overhead Intel RealSense D435i RGB-D camera, newborn placement, and the holder structure used during image acquisition [12]. The system enables fast, contact-free body length measurement using a single shot, with results displayed immediately on the monitor, thereby reducing stress on fragile newborns without direct contact.

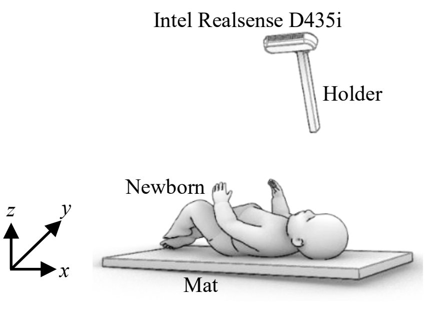


Fig. 1 Measurement System.

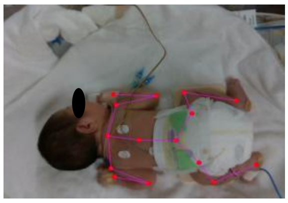
The proposed method consists of RGB-D image acquisition, YOLOv8-pose-based neonatal keypoint detection, 3D keypoint extraction, body-segment distance calculation, and final body-length estimation using AdaBoost regression.

3. Measurement Process

Firstly, a color image of the infant is captured, as shown in Figure 2(a). For pose estimation, the YOLOv8 pose detection model is used to detect 15 anatomical keypoints in the image. YOLOv8-pose is a lightweight, anchor-free network designed for real-time keypoint detection. Its single-stage architecture enables joint localization in a single forward pass, achieving results at speeds exceeding 30 FPS on common hardware [13,14]. The model is originally pretrained on large human-pose datasets and fine-tuned on our neonatal keypoint annotations, which improves robustness to small body sizes, different postures and varied lighting. Figure 2(b) presents the joint detection results. After detection, their (x, y, z) data for 3D coordinates are obtained for each keypoint from the corresponding location on depth image. After the 3D data joint conversion is completed to these locations, the length of the segment between each point is calculated and the body length is estimated using machine learning algorithm.

For YOLOv8-pose estimation, the total images (202 images) are partitioned into training-80% and testing-20% subsets. The training set is used to fine-tune the model on an NVIDIA GRTX A5500 GPU. Once training is completed, the final model is evaluated for real-time inference of keypoint detection on the captured images. The model achieved mAP of 72.5%, demonstrating reliable neonatal keypoint detection under practical NICU conditions.

(a) Captured image



(b) Keypoints detection

Fig. 2 Captured image, and joint detection results.

4. Experimental Results

The study focused on preterm infants with body weight below 1,500 g who required incubator-based care during measurement. A total of 435 images were collected from the NICU for body-length estimation between 20 September 2023 and 05 May 2024. The dataset was split into 75 % training data and 25 % testing data. In this case, we used two datasets because YOLOv8-pose needed for keypoint-annotated set, whereas AdaBoost trained on body-length features for length estimation; they serve different purposes.

We employ an AdaBoost ensemble to predict the newborn body length from the extracted distances between anatomical keypoints [15,16]. Ensemble learning combines many "weak" base learners—here, shallow decision trees—into a single strong predictor. In AdaBoost, each tree is trained sequentially, with later trees focusing more on examples that earlier ones mispredicted; their outputs are then weighted and summed. This approach reduces both bias and variance, yielding more accurate and robust length estimates even when individual measurements are noisy [17]. Therefore, AdaBoost is a good choice for our system which is difficult to avoid newborns different body conditions and postures. Mean absolute error (MAE) for the testing dataset is 2.75cm. Figure 3 shows the error distribution for manual and estimated measurements results. Manual body length measurements obtained by trained medical staff using a tape measure were used as ground-truth reference values for both training and validation of the AdaBoost regression model.

Some observed estimation errors are slightly higher in certain cases, primarily due to variations in newborn body posture while some estimations come out reliable results. In particular, differences in leg position, backward or upward body curvature, and varying degrees of knee flexion significantly affect the apparent body length in monocular images. Since preterm newborns naturally maintain a flexed posture and cannot be fully extended during measurement, these posture variations introduce additional challenges for accurate length estimation.

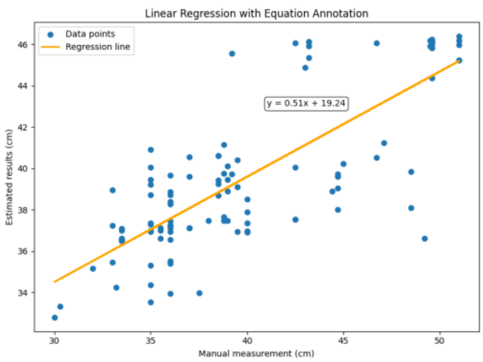
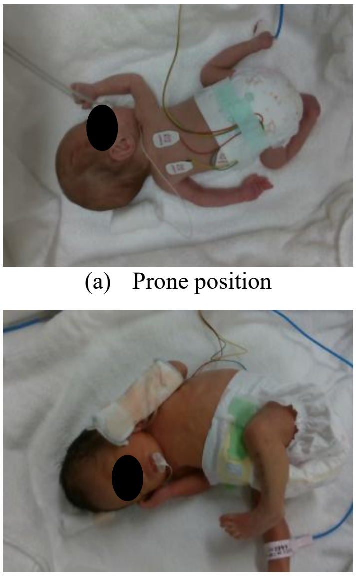


Fig. 3 Error Distribution.

During image acquisition, newborns were measured in both supine (upward-facing) and prone (downward-facing) positions depending on routine NICU care and the infant's condition. As preterm newborns naturally maintain flexed postures and cannot be safely straightened, posture variations were observed, including differences in leg positioning, backward or upward body curvature, and varying degrees of knee flexion. These variations affect the apparent body length in single-camera images and can contribute to estimation error in some cases as shown in Figure 4.

To address this limitation, future work will incorporate real-time posture analysis by classifying and correcting the orientation of newborn body postures before body length estimation, thereby improving robustness under varying leg positions and degrees of knee flexion.



(a) Prone position

(b) Supine position

Fig. 4 Samples of body positions and varying of knee flexion.

5 Conclusion

This study examines a compact, camera-based body length estimation system for preterm newborns in the NICU. YOLOv8 is used to detect newborn joint locations, and the distances between adjacent joints are subsequently computed. An AdaBoost ensemble model then estimates the overall body length. Although the proposed system demonstrates promising performance, some test samples exhibit relatively large estimation errors, which may limit its direct applicability in real-time clinical settings. These errors are primarily caused by significant variability in newborn body posture in the captured images. Posture variations such as leg positioning, backward or upward body curvature, and differing degrees of knee flexion affect the apparent body length in monocular images. To address these limitations, future work will incorporate real-time posture estimation by classifying and correcting newborn body orientation and knee flexion degree prior to body length estimation, with the aim of improving robustness and accuracy under varying posture conditions.

6 Acknowledgements

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