Development of Smart Phone-based Child Health Screening Tools for Community Health Workers

R. Fletcher, X. Soriano Díaz, H. Bajaj
MIT D-Lab
Massachusetts Institute of Technology (MIT)
Email: fletcher@media.mit.edu

S. Ghosh-Jerath
Public Health Foundation of India
Plot No. 47, Sector 44, Institutional Area
Gurgaon, India

***Abstract*—Child health screening is a fundamental component of public health, which includes neonatal screening, detection of infectious diseases and monitoring of nutritional status. Unfortunately, the tools to perform these tasks are often very crude, requiring manual input of data which is prone to error and falsification. Furthermore, the staff which performs these duties often lack clinical training or education. To meet this need, we have developed a low-cost child screening platform, called Baby Naapp, which enables community health workers to automatically collect data from a child without the need for any manual input. Making use of the smart phone camera, machine vision software, and augmented reality, our mobile app tools automatically measures a baby's height and weight just using a traditional weighing scale and a custom baby blanket. We have also developed a camera-based app which automatically records the child's Middle Upper Arm Circumference (MUAC), which is a standard measurement for assessing malnutrition. In addition, we have also integrated a custom pulse oximeter device to measure a baby's heart rate and heart rate variability, and we have integrated a low-cost thermal camera module to assess a baby's thermal regulation and potentially screen for infections. All measurements are recorded digitally and uploaded to a central server for use by clinicians and the local public health officials. The software for baby height, weight, and MUAC have been validated in the laboratory setting against manual measurements, with measured errors of +/- 1.2cm for height, +/- 90 grams for weight, and +/- 2.0 mm for MUAC. We are currently conducting a 4-month feasibility study of these tools with 13 ASHA workers in an urban slum area of New Delhi, India, in collaboration with the local government and the Public Health Foundation of India.**

Keywords—community health workers, child, baby, height, weight, MUAC, thermal, oximeter, screening, global health, mobile phone, augmented reality, ICTD.

I. INTRODUCTION

A. *Importance of Child Health Screening*

Child health is a fundamental indicator for international development. Children represent the most vulnerable segment of the world's population, and assessment of child health is critical to ensuring a healthy population in any country. International initiatives, such as the United Nations Millennium Development Goals (2000), and more recently, the Sustainable Development Goals (2015), have both identified child health as an international priority [1].

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Figure 1 . Examples of mobile software tools to measure infant weight (left) and height (right) which are described in this paper.

B. *Traditional Metrics for Child Health*

In terms of mortality, the leading causes of death for children under 5 years of age are infectious diseases (e.g. pneumonia, diarrhea, malaria, measles) and malnutrition.

While the assessment tools and metrics for child health vary as a function of socioeconomic status and type of clinical facility, certain fundamental metrics are common worldwide, even in low-resource settings. These traditional metrics include: weight, height, temperature, and middle-upper arm circumference (MUAC) [2]. Anthropometric and physiological measurements begin at birth with neonatal screening, to identify potential congenital disorders or developmental challenges, such as prematurity. However, after the first few days of life, a child's health assessment generally shifts to monitoring the child's growth and nutrition status as well as to identify signs of potential infectious disease.

Several international organizations, such as the World Health Organization (WHO) and UNICEF have published guidelines for child health assessment in an effort to standardize practice and improve data quality [3-4]. These guidelines are used by primary care clinics, community health workers and health camps worldwide.

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C. *The Role of Community Health Workers*

Many developing countries in Africa, Southeast Asia, and Latin America, child health screening is often performed by community health workers (also known as frontline health workers), which can be part of various public or private initiatives. These community health workers, nurses and midwives, are the first and often the only link to health care for billions of people living in the developing world; they are critical in settings where the overall primary health care system is weak or inaccessible.

Most community health workers do not have any office or clinic, but simply go door-to-door, providing education, counselling, health screening, and referrals for institutional check-ups. In India specifically, the National Health Mission operates a community health worker program which consists of ASHA workers (Accredited Social Health Activist). These local women are nominated from their own community and receive some basic training for home-based newborn care (HBNC), and Reproductive, Maternal, Newborn, Child, and Adolescent Health (RMNCHA) services. The ASHA program was initially implemented in rural areas throughout India but is now being adopted in many poor urban slum areas as well [5]. An older health worker program, Anganwadi workers (AWW), operated by the Ministry of Women and Child Development, also looks after child nutrition, but operates out of a centralized facility with less emphasis on home visits.

D. *Challenges in child health assessment*

Despite the existence of international guidelines, the quality of child health screening can vary widely, even across parts of the same country. As an example, members of our team have travelled to rural clinics in over 14 states in India, and observed many challenges, including the following:

- *Lack of tools*: Although a basic set of tools and medicines are supposed to be provided to the Indian ASHA workers [6], in practice many of these tools are missing and have low quality. As a result, measurements are often estimated or prone to error [7].
- *Lack of digital records*: In most areas, data is collected manually and recorded on paper, which is prone to error and limits the ability to for analysis or integration with electronic medical records.
- *Lack of expertise and education*: Since the health workers themselves have very limited education and clinical expertise, the integration and adoption of any technology is also limited.

Taken together, these challenges often result in a lack of capacity to detect early signs of disease or pathological conditions. More importantly, the lack of quantitative tools limit the ability for an uneducated health worker to motivate a child's family to take action or instill health-seeking behaviors. Generating a demand for health services is ultimately limited by the ability of a community to properly assess a child's health.

E. *Proposed solution and focus of this paper*

In this paper, we explore the design and validation of a new generation of tools for health assessment, which make use of ubiquitous low-cost smart phones. We have integrated several software tools into a mobile platform which we call Baby Naapp. This toolkit automates existing measurements and also introduces new clinical measures that are generally not used with low-skilled health workers. The design and validation of the individual tools are described in the sections below.

II. RELATED WORK AND LIMITATIONS

Over the past decade, a variety of mobile health, or mHealth, initiatives have emerged throughout the world [7], as smart phones slowly replace feature phones in many developing countries. But although smart phones contain integrated high resolution cameras, motion sensors, and impressive computational power, the primary use of phones has remained limited to text messaging services, manual data collection, interfacing to electronic medical records, and a few biomedical peripherals (e.g. microscope) for lab diagnostics. Very little has been published on the use of mobile apps that *automatically* collect anthropometric and physiological data for child health assessment in the hands of community health workers.

A sample of existing mobile phone based tools applied to maternal and child health are mentioned below:

A. *Text message systems*

Server-based SMS text messaging systems such as Child Count+ [8] and mMitra [9] are used to deliver maternal and child health information to mothers, and provide epidemiological data for use by the local government.

B. *Toolkits*

Some higher-cost diagnostic hardware toolkits, such as Care Mother [10], include commercial biomedical devices (Doppler ultrasound device, blood pressure monitor, and electronic glucose meter, urinalysis), which are used to help identify and prevent high risk pregnancies.

C. *Mobile Health Data Collection Platforms*

Many small companies, such as Dimagi [11], Mobilitas [12], as well as government initiatives such as M-Sehat [13], now offer software platforms that support case management and integrate with electronic medical record systems.

Many academic research projects and initiatives have also been developed for community health workers that leverage the increasing availability of smart phones. These mobile apps have generally been created to help simplify the task of survey-based data collection [14-15], mobile telemedicine [16], and also to help incentivize the health workers themselves [17].

Despite the existence of all these mobile platforms, all data collection requires manual data entry (e.g. typing in the glucose reading, or the baby's height and weight). Given this context, we have identified the need to create a next-generation of mobile tools that can make use of the intrinsic capability of smart phones to automatically make measurements without the need for manual data entry.

III. CHILD ASSESSMENT KIT DESIGN

A. *Main Application: Baby Naapp*

Our mobile toolkit was developed for Android phones and was given the name Baby Naapp, as an allusion to the Hindi word "naap" which means "measurement". Baby Naapp [Figure 2] is comprised of several basic tools for traditional child health assessment, as well as more advanced tools that could be used in the future to screen for disease or abnormalities. The operation and technical design of these tools are discussed separately in the sections below.

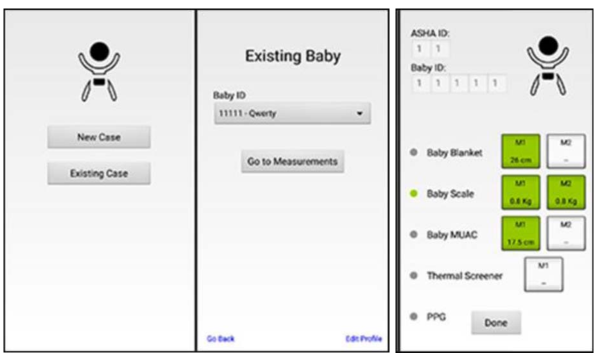

Figure 2 . Screenshots of Baby Naapp. The image on the right shows the main screen that is used to launch the individual tools for child assessment.

B. *Infant Height*

By using a specially-marked blanket, upon which the baby is placed, the baby's height can be automatically measured by the phone. Unlike other camera-based approaches that require significant calibration or sensor measurements [18-20], our tool makes use of machine vision and augmented reality to automatically correct for geometric and parallax distortion.

Automated tracking and detection is made possible through the use of an optical pattern or Augmented Reality (AR) target. For the baby blanket, we designed an AR target in the form of traditional Indian drawings of animals which were distributed on three sides of the blanket. The fourth side is left blank so that the arms of the mother would not occlude the pattern while stretching the legs and holding down the arms of the baby. Thin horizontal blue lines were also added as a guide for placing the baby on the blanket. Our design (Figures 3 and 4) provides the children, mothers, and ASHAs with a more natural and familiar user experience.

Figure 3 . Baby doll being held on blanket while smartphone captures baby's height

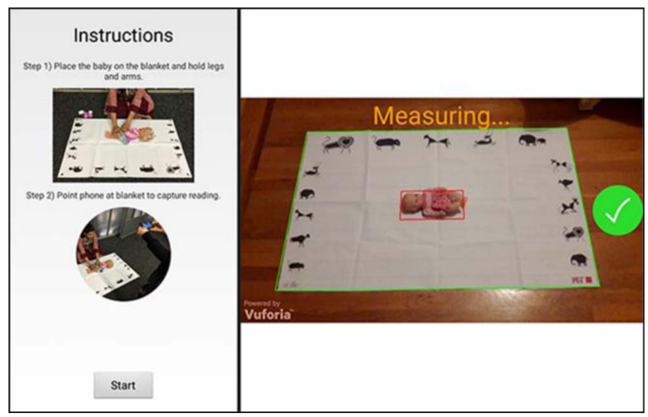

Figure 4 . Screenshots of the baby blanket app tool used to measure child length/height.

Our machine vision software makes use of the Vuforia SDK, which enables automatic tracking, corrects for parallax distortion, and computes the distance to the blanket surface. The OpenCV Library is used to perform a rectification of the target and to extract the image segment which contains the baby. Denoising and blob detection is then applied to create a bounding box surrounding the baby, and luminance adjustment is made to white-out any gray shadows present in the image. Morphological operations of dilation and erosion with a small square kernel were implemented to filter out the guidelines printed on the blanket and reduce unwanted noise. Given that the real dimensions of the blanket are known, the dimensions of the baby are calculated by comparing the ratio between the baby bounding box and the size of the blanket in pixels. The augmented reality library is used to display the outline of the blanket and the outline of the baby, as feedback to the user. Finally, once a stable reading is available (delay of approximately 0.5 – 1 second, depending on focus time of the phone), we display a green checkmark on the screen to indicate to the health worker that she can press the button to save the reading.

C. Infant Weight

For measuring infant weight, we make use of the low-cost weighing scale that is issued by the government to the community health workers. Similarly to the baby height measurement, we use machine vision algorithms to capture a digital reading from the weighing scale. To enable the automated tracking, an AR target was designed in the form of a child-friendly tiger sticker, which was affixed to the body of the scale. Operation of the weighing scale software tool is shown in Figures 5 and 6.

In order to perform a measurement, the infant is placed in a pouch and hung from the scale. While one person (usually the mother) holds up the weighing scale and baby, the health worker launches the weighing scale app and points the phone camera at the weighing scale. As shown in Figure 6, the software first searches for the AR target and then extracts a segment of the image that contains the weighing scale. The amount of extension of the spring is measured by vertically scanning the image segment and detecting the top and bottom edges of the portion of the scale that protrudes from the main body. Dilation and erosion algorithms are applied to filter noise and unwanted colors in the image segment, such as printed text. Since the dimensions of the AR target are known, we can calculate the linear displacement of the spring and thus determine the weight of the baby.

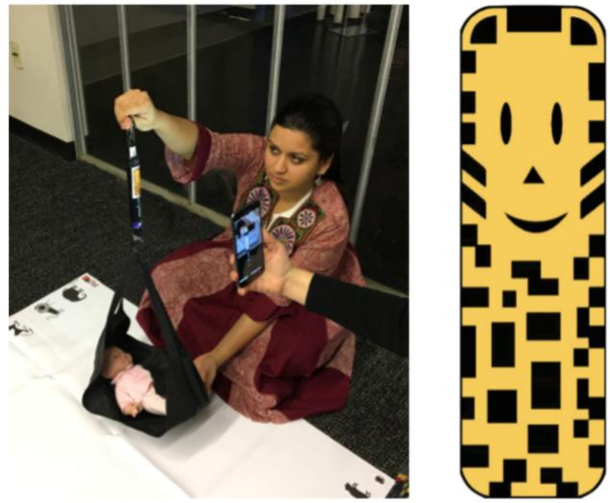

Figure 5 . (left) demonstration of weighing scale app; (right) child-friendly design for the augmented reality target used for weighing scale.

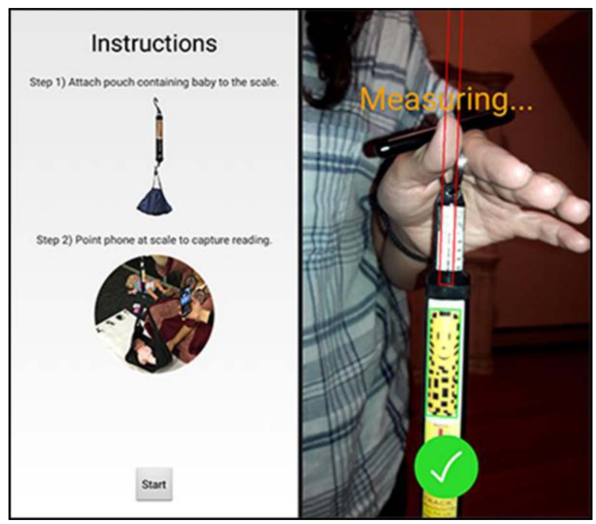

Figure 6. Screenshots of the Baby Scale application used to measure infant weight.

D. Infant MUAC

For the measurement of Middle Upper Arm Circumference (MUAC), a child-friendly custom measurement band was designed (Figure 7). Similar to conventional MUAC bands, our band design contains ruler markings in centimeters, and contains Red-Yellow-Green colored sections indicating malnourished, marginal, and normal. Therefore, the band could be used completely manually without a mobile phone. is measured at the midpoint of the child's radial bone, following the international guidelines [3].

In order the capture the reading digitally, we designed the "head" of the MUAC band to contain an AR target that enables optical tracking of the band. In between the eyes, is a measurement window which can be used for both manual and digital measurements. Each of the long edges of the band contains periodic black markings, which serve as a linear code. One edge has period T_1 and the other edge has period T_2. In our current band design which can measure circumferences from 4 to 25 cm, there are *n*=7 periods T_1 along one edge and there are *n*=8 periods T_2 along the other edge. The periods T_1 and T_2 were chosen such that the width of the measurement window would be greater than $T_1/2$ and $T_2/2$.

In order to calculate circumference, the MUAC software focuses inside the measurement window, and analyzes the phase difference between the black markings on each edge of the band. In order to explain how the circumference, *d*, is derived, we can define the edges of the black markings as having a *rising edge* and a *falling edge*, with period T_1 and T_2, respectively. As shown in Figure 7, let $L_1$and L_2 be the distances from the center of the measuring to window to the next rising edges of T_1 and T_2, respectively. It is easy to observe that *d* can be written as:

$$d = m_1 T_1 - L_1 = m_2 T_2 - L_2$$

Where m_1 and m_2 is a pair of positive integers for which it can be trivially verified that $m_1 \leq m_2 \leq m_1 + 1$, resulting in these two cases:

- **Case 1:** $m_1 = m_2$

$$m_1 = \;\; n + 1 \;\; \frac{L_1 - L_2}{T_1}$$

- **Case 2:** $m_1 = m_2 - 1$

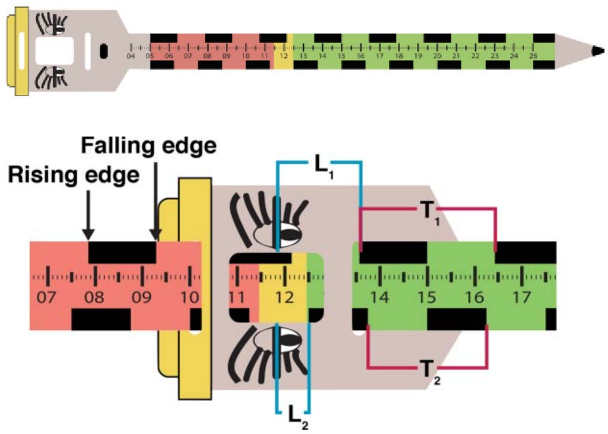

Figure 7. (top) photo of MUAC band showing child-friendly design; (bottom) close-up detail of the "head" of MUAC band which integrates the augmented reality target and optical linear code used to calculate the position along the band.

$$m_1 = \; n + 1 \; \frac{(L_1 - L_2)}{T_1} + n$$

The MUAC software tool (Figure 8) finds the rising edges by scanning the image segment and detecting abrupt changes in brightness. If the rising edge is found to the left of the center, a full period is added to infer the next rising edge. Alternatively, when a falling edge is found, half a period is added.

Since the MUAC band is not flat, but rather wrapped around a child's arm, an additional correction must be added to our algorithm to account for curvature. Since the curvature is not fixed, this can be solved by implementing an iterative algorithm which makes an initial estimate and then iteratively converges on a corrected value. Starting with an initial circumference estimate of 15cm, our correction step uses the measured distances that are projected into the camera plane to correct the circumference value. This new circumference estimate is then saved and the algorithm continues to iterate until the measurement converges to within 1mm.

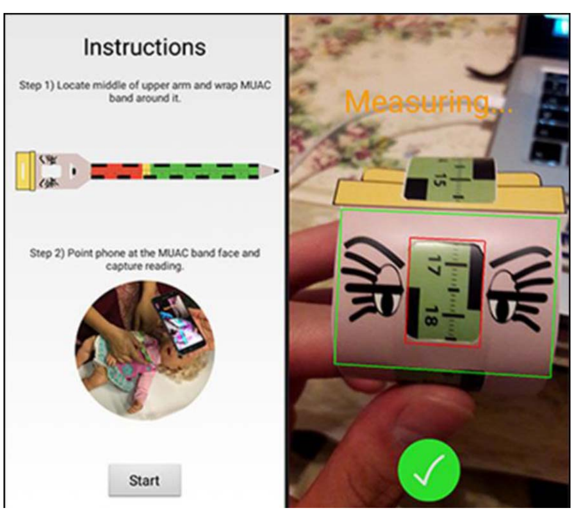

Figure 8 . Screenshots of the MUAC measurement app.

Figure 9 . MUAC measurement application being used by health worker.

For the health worker, the procedure for capturing the MUAC reading is to first find the midpoint of the humerus bone, then apply the band at that point, and then launch the MUAC tool and point the phone camera at the band. A green check mark appears to indicate to the health worker when it is OK to press the button to save the measurement.

E. Thermal Assessment

The thermal regulation of a neonate is critical for survival and its measurement can be an indicator of pathophysiology [21]. Thus, we chose to also include thermal analysis as an additional tool for child health assessment. As part of other collaborative work from our group, it has been recently demonstrated that thermal imaging can be a useful tool in detecting hemodynamic

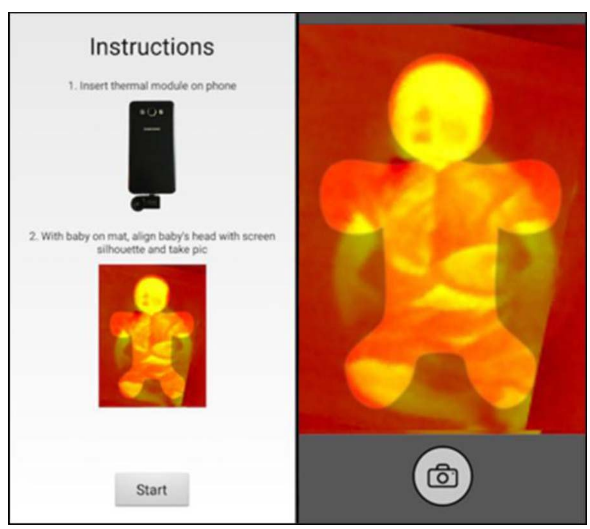

Figure 10. Screenshots of the Baby Thermal App. On the rightmost screen, the head of the baby has been aligned with the head of the baby silhouette.

conditions such as circulatory shock and sepsis [22]. Thermal imaging has also been demonstrated as a screening tool for pneumonia [23], and other groups have demonstrated the use of thermal imaging to measure the respiration in infants [24].

For implementation, we made use of a commercial USB thermal imaging module designed for use with mobile phones (Seek Thermal Compact), which has a pixel resolution of 206x156, shown in Figure 10. A custom mobile app was created that enables the health worker to quickly capture a thermal image of the infant that is lying in supine position. Computer vision algorithms were implemented that enable both the thermal (IR) image to be captured simultaneously with the visible image and maintain registration between the 2 images. This enables us to make use of machine vision face/body recognition tools to automatically find points on a the infant's face and body. For guiding the health worker, a silhouette of a child's body is superimposed on the thermal imaging screen, and the health worker was instructed to make sure that the baby's head is aligned with the silhouette. This helps ensure that the infant will be centered in the image and that the distance to the infant will be consistent.

Since the thermal camera image only has 8 bits of resolution, our mobile app also records an array of values giving precise temperature values for each pixel. This file is simultaneously captured together with the visible and thermal image, and is what we use for analysis.

E. Cardiac Assessment

Cardiac assessment is fundamentally important for newborns and infants. Photoplethysmography (PPG) and pulse oximetry are standard tools for pediatric care [25] and the value of PPG devices has been demonstrated in global health [26] for congenital abnormalities [27] and screening for sepsis and infectious diseases [28]. Few tools are currently available for this application, such as [29], currently only for Apple phones and tablets.

We developed a custom PPG device [Figure 11], for use with Android phones, which contains 3 different illumination wavelengths and is capable of measuring both reflected and transmitted light from a baby's foot. This device does not require batteries and plugs into the USB port on the phone. An adaptable custom probe was also designed so it could be wrapped around a neonate's foot as well as an older child's finger. While this tool has many potential applications, for the purpose of the current study, we have initially implemented heart rate and heart rate variability for field use, with other measurements (e.g. PO2SAT) being reserved for clinical use, such as in a primary health clinic (PHC).

Figure 11. (left) Photo of custom PPG device connected to Android phone. (right) PPG device being applied to baby foot in a field study.

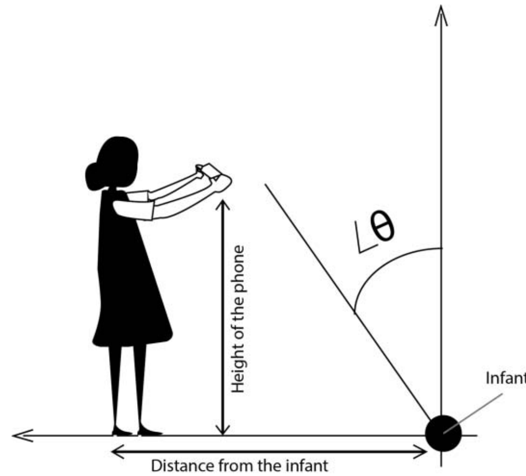

Figure 12. Illustration showing the variables that were used for testing.

IV. TESTING AND VALIDATION

All tools in the Baby Naapp kit were first tested and validated in the laboratory. All tests were conducted using the Samsung J7 phone, which is a lower cost model available in developing countries. Two portable compact fluorescent floor lamps were used, allowing us to test with different lighting levels and camera angles. The testing for each tool is described below.

A. Infant Height

For testing the height measurement tool, two custom baby dolls were built, with each having adjustable length. The tool was tested with the special blanket over a range of light settings (Lux = 25, 50, 100, 500) and phone camera angles (see Figure 11), with θ = 0, 15, 30, 45, and 60 degrees, and phone height kept <50cm. Results are shown in Figure 13 and Figure 14.

ID	∠ Angle	Distance from baby (cm)	Height of the phone (cm)	Mean	Standard deviation	Mean error
1	0	0	48.03	60.93	0.09	0.426
2	15	31	46.06	61.36	0.13	0.864
3	30	63	43.3	61.66	0.10	1.158
4	45	90	35.43	61.97	0.09	1.466
5	60	135	30.7	64.10	3.73	3.604

Figure 13.Testing for angle-dependent variations at a constant lighting of approximately 500 Lux. The actual length of the baby doll was 60.5 cm, measured manually.

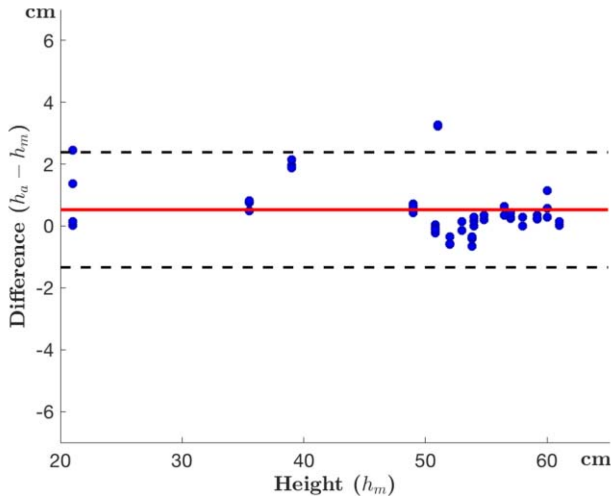

Figure 14. Bland-Altman plot comparing the manual measurement of the baby's height vs. the app measurement for a range of heights.

As shown in Figure 13, for moderate angles of 0-30 degrees, the mean error remained within 1.2 cm. At 45 degrees, the error was still reasonable, and at the extreme angle of 60 degrees, the mean error increased significantly to 3.6cm. This demonstrates that our machine vision algorithm is successfully able to compensate for camera angle provided that the camera angle is not large (<30 degrees).

The performance of our baby height measurement tool was then tested under different levels of lighting (Lux = 25, 50, 100, and 500) with a camera angle of 30 degrees. These lighting levels are fairly dim compared to typical office lighting, but is typical of most households in poorer homes. Our experiments showed that the mean error remained fairly constant within ~1.5 cm for levels of 50 lux and above. At 25 lux, however, which is equivalent to the illumination of a few candles, the mean error increased to 2.4cm. This finding shows that for very dark rooms, our tool would require some external illumination, such as solar light carried by the health worker.

B. *Infant Weight*

For testing the weighing scale application, the scale was hung form a tripod and several discrete calibrated weights were used to test our tool in the range 0 to 5 kg. The results showing the measured weight with the actual weight are shown in Figure 15.

Below 4.7 kg, the weight measurement tool performed reasonably well, remaining with 200 grams of the actual weight, and with a mean error of 90 grams. At the end of the weight scale range, for weights 4.7-5 kg, a larger error was observed, mainly due to the large extension of the weighing scale and geometric distortion.

Unlike the height measurement tool, the weighing tool is used by holding the phone fairly close to the AR target (as shown in Figure 5). Therefore, it was possible to use

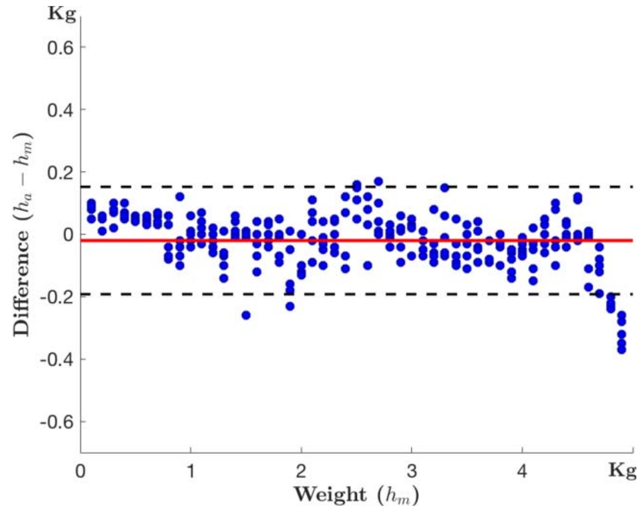

Figure 15. Bland-Altman plot that compares the manual measurement of the baby's weight vs. the app measurement for a range of weights.

the integrated flash from the smart phone to assist in cases with low illumination. We tested performance over a range of ambient lighting levels (Lux = 25, 50, 100, and 500), and found no noticeable degradation in the reading performance.

C. *MUAC*

The MUAC measurement tool was tested using a variety of large plastic hose available in the lab as well as manually adjusting the MUAC band. The MUAC value measured by the mobile app was compared against the actual value, and the results are shown in Figure 16.

Over the entire measurement range (8cm – 24cm), good agreement was found between the measured and actual results, with mean error of ~ 0.18cm. A few outlier points were observed in the extreme low end of the circumference range (<8.2cm), likely due to the increased curvature of the AR target which distorts the geometric calculation. This issue is being addressed by slightly reducing the vertical height of the AR target in the next version of our MUAC band.

For the MUAC tool, the integrated flash was turned OFF to avoid specular reflections and glare that interfered with the measurement. Testing was conducted a circumferences of 11cm, 13cm, and 16cm, over a range of illumination levels (Lux = 25, 50, 100, and 500). For illumination of 50 Lux and greater, the mean measurement error remained under 0.2cm. However, at 25 Lux the error increased to 0.4cm. Given this result, similarly to the height measurement tool, an additional light source may be required if this tools is used in home with very dim lighting (<50 Lux).

D. *Thermal Assessment*

The thermal measurement tool was validated by using a large 12in x 12in hotplate used for electronics soldering, and using automatic emissivity adjustment on the thermal camera module. The hotplate temperature was varied over 20 discrete values between 20 °C – 40 °C, and the measured reading with the thermal camera were found to be within 0.1°C, which was the limit of resolution for the hotplate.

E. Cardiac Assessment

Our PPG tool was compared against an FDA approved pulse oximeter (Nonin Onyx II model 9560), on two children, age 8 months and 19 months. The measured heart

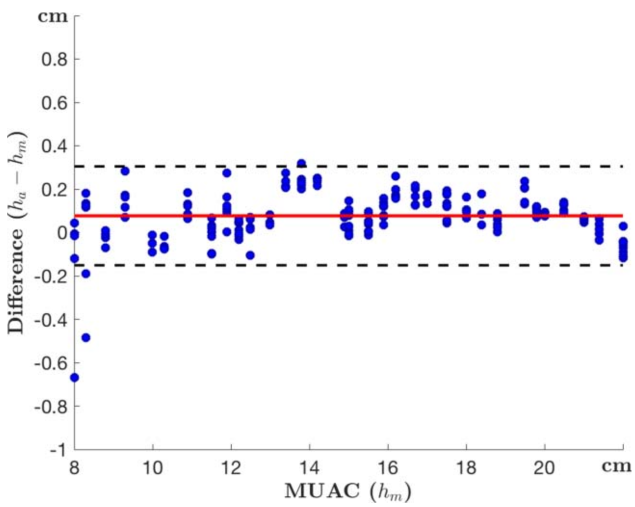

Figure 16. Bland-Altman plot comparing the measured MUAC value against the actual measurement .

rate readings from our PPG device and software were within 4ppm of the readings from the commercial device.

V. DISCUSSION AND FIELD TESTING

A. Acceptable Levels of Error

The results of our laboratory testing are encouraging and demonstrate good accuracy compared with manual measurements. However, we also identified one clear disadvantage of using camera-based measurements, which is the degradation of performance under very low lighting levels. As mentioned previously, settings with very dim lighting (<50 lux) may require the health worker to carry some type of light source, such as a solar charged lantern.

The acceptable levels of error for each measurement depend on the specific application. For the purpose of screening for malnutrition assessment, for example, it is often sufficient to know if the child is one or two standard deviations from the normal growth curves (weight, height, and MUAC). The measured error in our tools are sufficient to meet these criteria.

A. Usability Testing

In order to test the performance of our tools in the hands of actual health workers in realistic field conditions, we created a Hindi-language version of our mobile apps, with data uploading to a central server, and we are currently conducting a 4-month field test with 13 community health workers in an urban slum area of New Delhi, India. The results of that study along with usability data, and qualitative feedback shall be presented in a future publication.

VI. CONCLUSION

We have designed and demonstrated a low cost child health assessment kit, Baby Naapp that can be implemented on a mobile smart phone with very inexpensive peripherals. Based on laboratory testing, the tools included in the kit compare favorably against the traditional manual measurements.

In addition to the basic tools for conducting anthropometric measurements, we have also demonstrated the design of more advanced tools for health assessment (thermal imaging and photoplethysmography), which could be used by community health workers and staff in primary care clinics as diagnostic and screening tools. We are currently exploring additional measurements that could be implemented with our Baby Naapp tool kit, including bilirubin measurement for jaundice screening as well as hemoglobin measurement for anemia assessment.

Given the increasing use of smart phones among community health workers, mobile tools such as these hold great promise toward improving the accuracy of child health assessment, and also present new opportunities to monitor health and screen for diseases in low-resource areas around the world.

ACKNOWLEDGMENTS

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REFERENCES

[1] United Nations Sustainability Goals, available online: http://www.un.org/sustainabledevelopment/sustainable-development-goals/
[2] Briend, André, Bernard Maire, Olivier Fontaine, and Michel Garenne. "Mid-upper arm circumference and weight-for-height to identify high-risk malnourished under-five children." *Maternal & Child Nutrition* 8, no. 1 (2012): 130-133.
[3] WHO Child Growth Assessment Guidelines, available online: http://www.who.int/childgrowth/en/
[4] "Training Course on Child Growth Assessment," Published by WHO, 2008. Available online: http://www.who.int/childgrowth/training/module_b_measuring_growth.pdf? ua=1
[5] "*Home Based Newborn Care: Operational Guidelines*," published by Ministry of health and family Welfare, Government of India, 2014, Available online: http://dshm.delhi.gov.in/pdf/guideline/Revised_HBNC_Operational_Guidelines_2014_English.pdf
[6] http://nhm.gov.in/communitisation/asha/list-of-drugs-being-provided-in-asha-kit.html
[7] Ulijaszek, Stanley J., and Deborah A. Kerr. "Anthropometric measurement error and the assessment of nutritional status." *British Journal of Nutrition* 82, no. 3(1999): 165-177.
[8] http://www.childcount.org/
[9] http://www.mmitra.org/
[10] http://www.caremother.in/index.aspx

[11] http://ww.dimagi.com
[12] http://mobilitas.co
[13] http://msehat.in/
[14] https://opendatakit.org/
[15] Brunette, Waylon, Mitchell Sundt, Nicola Dell, Rohit Chaudhri, Nathan Breit, and Gaetano Borriello. "Open data kit 2.0: Expanding and Refining Information Services For Developing Regions." In *Proceedings of the 14th Workshop on Mobile Computing Systems and Applications*, p. 10. ACM, 2013.
[16] http://dev.sanamobile.org
[17] DeRenzi, B., Dell, N., Wacksman, J., Lee, S., & Lesh, N. (2017, May), "Supporting Community Health Workers in India through Voice-and Web-Based Feedback"; *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM.
[18] http://www.caramba-apps.com/easymeasure/
[19] Laotrakunchai, Suraphol, Akarapas Wongkaew, and Karn Patanukhom. "Measurement of size and distance of objects using mobile devices." In Signal-Image Technology & Internet-Based Systems (SITIS), 2013 International Conference on, pp. 156-161. IEEE, 2013.
[20] Han, Dianyuan, and Chengduan Wang. "Tree height measurement based on image processing embedded in smart mobile phone." In Multimedia Technology (ICMT), 2011 International Conference on, pp. 3293-3296. IEEE, 2011.
[21] Lunze, K., and D. H. Hamer. "Thermal protection of the newborn in resource-limited environments." Journal of Perinatology 32, no. 5 (2012): 317-324
[22] Sethi, Tavpritesh, Aditya Nagori, Ambika Bhatnagar, Priyanka Gupta, Richard Fletcher, and Rakesh Lodha. "Validating the Tele-diagnostic Potential of Affordable Thermography in a Big-data Data-enabled ICU." In Proceedings of the Special Collection on eGovernment Innovations in India, pp. 64-69. ACM, 2017.
[23] Zhang, Biao. "Decision analysis of novel point-of-care diagnostics for Pediatric Pneumonia: implementation in Developing countries with tiered healthcare systems." PhD thesis, Massachusetts Institute of Technology, 2015.
[24] Pereira, C. B., Yu, X., Czaplik, M., Rossaint, R., Blazek, V., & Leonhardt, S., "Remote monitoring of breathing dynamics using infrared thermography," Biomedical Optics Express, 2015.
[25] Fouzas, Sotirios, Kostas N. Priftis, and Michael B. Anthracopoulos. "Pulse oximetry in pediatric practice." Pediatrics 128, no. 4 (2011).
[26] Duke, T., R. Subhi, D. Peel, and B. Frey. "Pulse oximetry: technology to reduce child mortality in developing countries." Annals of tropical paediatrics 29, no. 3 (2009): 165-175.
[27] Zhao, Qu-ming, Xiao-jing Ma, Xiao-ling Ge, Fang Liu, Wei-li Yan, Lin Wu, Ming Ye et al. "Pulse oximetry with clinical assessment to screen for congenital heart disease in neonates in China: a prospective study." The Lancet 384, no. 9945 (2014): 747-754.
[28] Weber, Martin W., John B. Carlin, Salvacion Gatchalian, Deborah Lehmann, Lulu Muhe, E. Kim Mulholland, and WHO Young Infants Study Group. "Predictors of neonatal sepsis in developing countries." The Pediatric infectious disease journal 22, no. 8 (2003): 711-717.
[29] Lions Gate Medical: http://lgtmedical.com/