The BabyView Camera: Designing a New Head-mounted Camera to Capture Children's Early Social and Visual Environment

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Abstract

Head-mounted cameras have been used in developmental psychology research for more than a decade to provide a rich and comprehensive view of what infants see during their everyday experiences. However, variation between these devices has limited the field's ability to compare results across studies and across labs. Further, the video data captured by these cameras to date has been relatively low-resolution, limiting how well machine learning algorithms can operate over these rich video data. Here, we provide a well-tested and easily constructed design for a head-mounted camera assembly—the BabyView—developed in collaboration with Daylight Design, LLC., a professional product design firm. The BabyView collects high-resolution video, accelerometer, and gyroscope data from children approximately 6 - 30 months of age via a GoPro camera custom mounted on a soft child-safety helmet. The BabyView also captures a large, portrait-oriented vertical field-of-view that encompasses both children's interactions with objects and with their social partners. We detail our protocols for video data management and for handling sensitive data from home environments. We also provide customizable materials for onboarding families with the BabyView. We hope that these materials will encourage the wide adoption of the BabyView, allowing the field to collect high-resolution data that can link children's everyday environments with their learning outcomes.

Introduction

What do babies and young children see during their everyday experiences? For more than a decade, researchers have made use of head-mounted cameras to understand what is in view for infants (i.e., an egocentric perspective) as they embark on learning from and about the world around them (Aslin, 2009; Smith et al., 2015; Yoshida & Smith, 2008). Head-mounted cameras provide a method for characterizing the visual environment (e.g., Fausey et al., 2016; Long et al., 2021) and understanding developmental changes in the child's perspective (Kretch et al., 2014). Studies using these cameras have collectively revealed that the view of an infant is quite different from that of an adult (Yoshida & Smith, 2008), with hands and objects encroaching dramatically on the field of view in ways that feel quite alien to adults.

Head-mounted camera datasets are also a valuable resource for secondary analysis. Advances in computer vision techniques can allow new automated annotation of these videos, removing some of the major challenges of working with larger video datasets and allowing insights into the consistency and variability of children's environmental input (Long et al., 2022a, 2022b). Further, due to dramatic advances in unsupervised learning models, new learning algorithms can be fit directly to these datasets, assessing what can be learned by different classes of algorithms as applied to infants' naturalistic inputs (Orhan et al., 2020; Zhuang et al., 2021). These advances coincide with a growth in interest in egocentric video in the broader computer vision community (e.g., Nagarajan & Grauman, 2021).

Despite these exciting applications, there is a paucity of publicly-available head-mounted camera data from children, with some notable exceptions. For example, the SAYCam dataset provides deep longitudinal data on three children from 6 to 32 months of age recorded in the naturalistic home environment (Sullivan et al., 2020) and the SEEDLingS dataset provides a cross-sectional sample of infant development from 6 to 18 months of age (Bergelson & Aslin, 2017). Finally, some smaller studies have shared in-lab videos (Franchak et al., 2011, 2017; Long, Sanchez, et al., 2022). However, the substantial privacy restrictions on developmental video data sharing have limited the amount of data available. Rather than relying on shared, open source databases, most researchers opt for collecting new, custom datasets (Clerkin et al., 2017; Fausey et al., 2016; Long et al., 2022a; Sugden et al., 2014). These datasets are often collected using procedures that are developed in-house, with different devices used in each study.

Variation between head-camera devices poses several substantial issues for the field. First, device resolution and field of view (FoV) vary widely between studies (see Table 1). If a goal of the research literature is to provide information about what is in the field of view (e.g. social information about parents' faces; Fausey et al., 2016; Long et al., 2022), it is quite problematic that the degrees of visual angle in the vertical field of view of the various cameras used in different studies might vary by up to a factor of two. Second, variation in resolution, image quality, and audio quality is potentially problematic for the application of computer vision techniques since differences between training and evaluation data can lead to substantial decreases in accuracy (Long et al., 2022a, 2022b). Third, because of FoV limitations, head-mounted cameras typically only capture children's interactions either with objects (when the camera is pointed down) or with their social partners (when the camera is pointed up), limiting researchers' ability to understand how these sources of information interact during learning. Finally, and perhaps most importantly, if a new lab hopes to adopt the head-camera method for a particular developmental population, there is no single device and procedure that is widely available and easy to adopt – thus, labs must constantly "reinvent the wheel."

Our goal in the current paper is to provide an openly available, well-tested design for a head-mounted camera, the BabyView, which can provide high-resolution video for children from approximately 6 - 30 months. We begin by discussing the desiderata around data quality, usability, and data management that motivated our design process. We then give an overview of the design process and specifications for the device, highlighting how the BabyView differs from devices used in prior work. We describe a data management workflow that accompanies the BabyView, as well as strategies for handling sensitive video data and meta-data. Finally, we review results from an initial pilot study testing the feasibility of this new design. All of the design specifications, recording instructions, and code for data management have been made publicly available at https://osf.io/kwvxu/. We hope that these materials will encourage the wide adoption of the BabyView by other groups and lead to the creation of reusable, egocentric video databases.

Design Criteria

Our group had previously created a large, longitudinal dataset of egocentric video from children (Sullivan et al., 2021) using a headband-mounted camera. This experience – as related by the parents in the study – convinced us that constructing further datasets would require a better camera, a safer and more comfortable mounting apparatus, as well as a less-burdensome data management pipeline. Thus, we began a design process in which we considered three classes of desiderata: (1) the quality of the data captured, (2) the usability of the camera by parents and children, and (3) the uploading and data management workflow.

Data quality. High data quality is critical for ensuring the scientific value of data from head-mounted cameras. Cameras need to record video in high-enough resolution to be useful for both human annotations and modern computer vision methods (e.g., for object recognition and semantic segmentation). While there is no strict resolution cutoff for such methods, past experience (e.g., with SAYcam data, in 480p i.e. 640x480 pixels) indicates that having a resolution of at least 720p (1280x720 pixels) makes smaller objects in the scene considerably more recognizable, a positive feature for both human annotators and computer vision methods. A further goal was to design a camera that also recorded accelerometer data, which can enable modeling of the child's head turns, locomotion, and possibly allow for reconstructing the child's 3D environment (Forster et al., 2016) However, the use of additional sensors (e.g. the accelerometer) and the highest possible resolution for videos typically require more battery power and makes videos very large and thus slow to upload. Thus, balancing resolution with battery life and transfer/upload time became an important consideration.

Our ability to quantify what is "in-view" for infants also depends critically on the view angle of the head-mounted cameras we use. To date, most cameras have had relatively limited field-of-view, forcing researchers to choose the view angle and camera mount angle best suited for a particular research question (see Table 1) and reducing generalizability. For example, while orienting a head-mounted camera slightly upward tends to capture views containing the faces of children's looming social partners, it does so at the expense of information about how children interact with the objects in front of them—either on their own or with their social partners. In our prior SAYCam project, we attached an aftermarket fish-eye lens to our cameras to increase the view angle—but this lens fell off intermittently, leading to data loss (and a choking hazard!). We sought to alleviate this issue by designing a head-mounted camera that records high-resolution video with a large FoV (see Figure 1), capturing both information about children's social partners and children's interactions with objects. Thus, our goal here was to standardize the angle at which the BabyView camera is mounted relative to the child's head to ensure that camera angles are similar when the device is worn by children of different ages or even by a single child across recording sessions.

Device	**FOV**	**Camera weight & size**	**Battery life**	**Resolution (pixels)**	**Extra Sensors**	**Flexible Sizing**	**Data Management**	**Availability and Price**
GoPro Hero Bones in BabyView	70° × 118°	86 g with battery, 50x68x29mm	45-60 min	1920 × 1080	Accelerometer and gyroscope	Yes – up to adult	Micro SD card to USB	$450 USD
Looxcie 2	69° × 41°	22 g 130x64x130mm	5 hours	720 × 480	–	Yes – ear clip	Flash storage to USB	Discontinued
Spycams	140-150° diag	Varies, similar to Veho Muvi	Unreliable	1280 × 720	–	Needs customized mount	SD card to USB	~
Veho Muvi Pro	74° diag	50g, 55x22x20mm	~80 min	640 x 480	–	Needs customized mount	SD card to USB	New version available with same FOV, $160
Narrative Clip 2	86° diag	19g 36x36x9 mm	~80 min	3264 x 2448	–	Clip for clothing	SD card to USB, Wi-Fi, Bluetooth	Out of stock
Pupil Core eye-tracker scene cam	139° × 83°	22.75g, 170x160x55mm	~	1920 × 1080	–	Yes– headband	Pupil Cloud; Invisible App transfer to PC	Only within custom eye-tracking system
Watec (WAT-230A) in headband	90°	30g 30x30x13mm	~	512 × 492	–	Yes– headband	Connection cable	Yes
PatrolEyes Mini	140°	104 g, 77x55x20mm	420 min	1920 × 1080	Night vision; waterproof	Clip for clothing	32GB internal storage; USB	$350

Table 1. Comparison of BabyView with infant head-mounted cameras used in prior research.

Ease of use. Head-mounted cameras are not easily tolerated by infants and toddlers, with many children pulling off the camera or simply refusing to wear it at all, leading to high rates of attrition in both in-lab and at-home studies. We thus aimed to design a device that was as comfortable and lightweight as possible when worn by young children of various ages so as to increase the likelihood that children would actually wear the camera for the desired length of time. In addition, we aimed to design a device that was sturdy and robust enough to withstand everyday use by caregivers with young infants and toddlers, especially important for large-scale or multi-year longitudinal studies.

Age range. Our primary goal was to construct a high-resolution head-mounted camera. However, high-resolution cameras tend to be larger and heavier than cameras typically used with infants less than 6 months of age; these smaller cameras typically have relatively poor resolutions and limited view angles (e.g., the Looxie 2, see Table 1). Thus, we anticipated that our youngest participants would be 6-month-old infants who are able to control their head movements and support a slightly heavier device, and we aimed to design a device that could be adapted for use from 6 – 30 months of age.

Data management. Given the large size of video recordings (e.g., a 3-minute video at 1080x1920 resolution is roughly 1GB), and the fact that studies will generally include multiple sessions from several families, video management is a challenging aspect of at-home video studies, both for participants and for researchers. Ideally, participants should be able to start a simple upload process to a secure server, flag any footage during recording that they are concerned about (e.g., private moments, unexpected visitors), as well as review and flag recently recorded videos at their leisure. Our goals were to streamline this process as much as possible, as well as limit the possibilities for data loss.

The BabyView Camera

Camera selection and orientation

We tested a large range of cameras capable of ~100° vertical FoV (including the RunCam 5, DJI Osmo Action, SJ4000, Insta360 Go II, GoPro 9, Yi 4K, GoPro HERO 8, GoPro HERO, and GoPro 10 Bones). Of these, the GoPros emerged as clear front-runners, given (1) gyroscope and accelerometer data, and (2) relatively high resolution sound and videos. We initially built a version of the BabyView using a deconstructed GoPro 8; however, the GoPro Hero Bones model – which was released during our design process – is the lightest weight GoPro camera and is already designed for use with a displaced battery, thus dramatically reducing the final cost of the build and improving robustness (see Figure 2a, 2b).

We experimented with orienting the camera vertically versus horizontally and with setting the camera angle to be neutral to the face plane of the child versus at a downward-facing angle. We chose a vertical orientation that was neutral to the face plane of the child, enabling the camera to capture both adult faces and objects within a child's hands in the same image, with an effective view angle of 100° vertical by 75° horizontal (see Figure 1 for a diagram and and Figures 3 and 5 for example images).

Apparatus construction

Camera mounting. Safety was a primary concern in our construction of the BabyView camera. For the camera mounting and battery enclosure, we chose a biodegradable, non-toxic 3D printed material (Polylactic acid, PLA; see Figure 2d), and we ensured that battery and board components would be separated from direct contact with skin; even so, we verified that the surface temperature of all parts of the apparatus did not exceed 120° F.

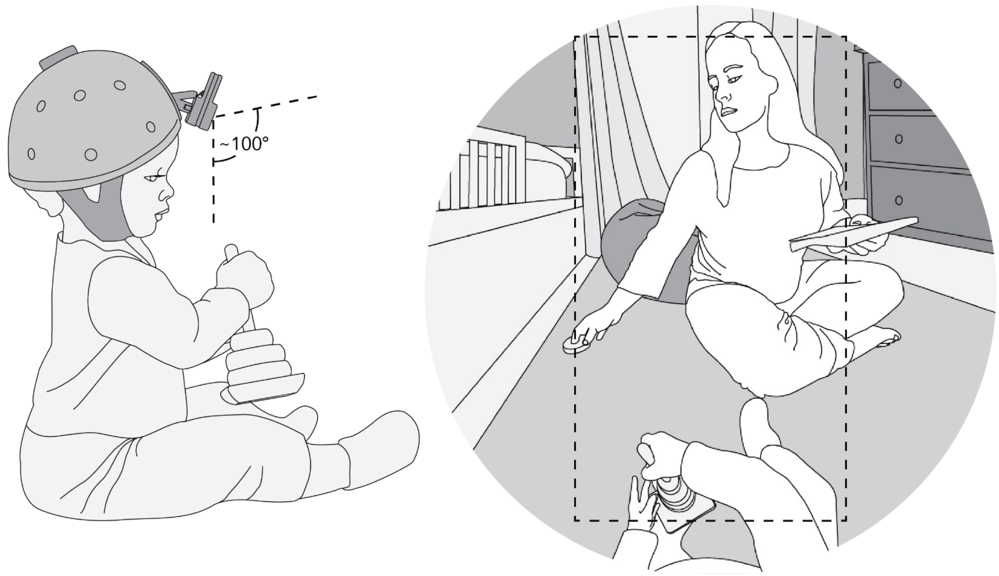

Figure 1. Schematic illustration of the BabyView camera's orientation (left) and field of view (right; dotted line), highlighting that this camera angle captures both the objects that children are interacting with as well as the social information in the child's view. See Figures 3 and 5 for example images.

Comfort and Safety. We explored different mounting alternatives to create a head-mounted camera that could be comfortably worn by children under the age of 3. We chose a helmet (Safehead baby, https://www.safehead.com/, see Figure 2c) that had already been designed and tested for safety, functionality, and comfort, and was able to accommodate a range of child head sizes (head circumference range: 40-52cm, helmet weight: 97 gms). In order to accommodate infants with smaller head sizes, we included an additional adjustment strap on the back of the soft helmet.

The helmet is placed on the child's head similar to how one would use a bicycle helmet and is secured with a soft chin strap. Initial pilot testing suggested that 1) children tolerated wearing the helmet better than head-lamp type designs used in our lab (e.g., Long et. al, 2022a) and 2) proper placement of the helmet was easy and repeatable. In addition, the helmet design allows the distribution of the combined weight of the camera (60 grams) and battery enclosures (26 grams) over the child's entire head. Formal and informal pediatrician consultations were conducted and all pediatricians expressed that the design as planned should not pose any risks to children's normal development. We used the typical weight of a corrective helmet designed for medical use in the treatment of plagiocephaly (on average ~225g) as a benchmark for a tolerable weight for the full apparatus. The final design was below this benchmark (206g total, including helmet, build materials, camera, and battery).

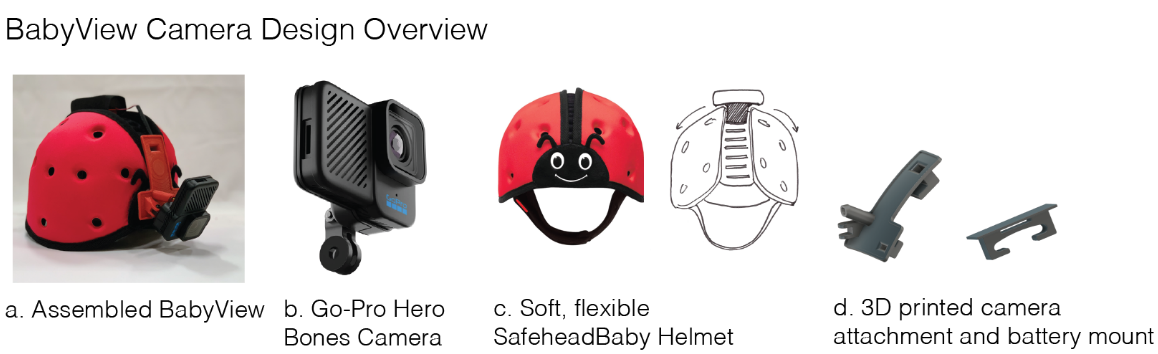

Figure 2. Overview of the BabyView Camera design process, showing (a) the assembled device, (b) the original camera, (c) babysafe helmet, and (d) and 3D printed mounting equipment.

Battery life & charging. Finding a lightweight, affordable, and rechargeable battery suitable for use with the BabyView was challenging. We explored many different lightweight battery options in order to power the GoPro Bones. We determined that a standard, rechargeable 9V battery was the most reliable, widely-available battery type; these batteries provide power to the BabyView camera for a continuous 45-60 minutes on a standard charge, while recording at

1080p and including accelerometer data.[1] In our current workflow, families are provided with three rechargeable batteries, which they are instructed to disconnect from the GoPro and charge after each use of more than 45 minutes. We also provide families with a backup set of non-rechargeable 9V batteries in case they forget to charge their rechargeable batteries.

Comparison to prior cameras

Our final apparatus design is shown in Figure 2a. In this configuration, the BabyView weighs 86 grams without the helmet and casing and ~206 grams when fully assembled. Table 1 shows a comparison of the BabyView camera to cameras used in prior studies and highlights the wide variability in the features of cameras available in the literature. Note that the BabyView camera has the largest vertical FoV and is the only camera with accelerometer and gyroscope data.

Figure 3. Comparison of the field-of-view and camera resolution between the Veho Muvi Pro (used in the SAYCam study) and the current BabyView design (i.e. GoPro Hero 10 Bones camera). Despite being at the same position, the Veho Muvi camera only captures a small

[1] Note that recording at very higher resolutions – while permitted by the GoPro camera – drain the battery and often cause the GoPro to overheat and automatically shut down. Innovations in lightweight batteries may alleviate this issue and could be attached to the GoPro without redesigning the BabyView camera enclosure and setup.

portion of the world within the child's view and reach; in prior work, an aftermarket fish-eye lens was attached to increase the field-of-view of the Veho. See Table 1 for dimensions.

In-Home Data Collection and Data Management

Since head-mounted cameras produce large volumes of video data, data management can present a significant challenge. Further, when the camera is often used in a family's home without experimenter supervision (e.g., as in the SAYCam study where parents recorded two sessions every week), the data upload process needs to be as simple as possible. We have thus designed a simple workflow for extracting data from the BabyView using a combination of the microSD card, a secure Google Drive upload system, and automated video preprocessing and archiving scripts. In this section, we present our workflows for in-home data collection, onboarding and data management.

Data collection

Participant onboarding. To improve retention and users' overall familiarity with the device and procedure, we recommend a video-chat or in-person onboarding session between the research team and the participant. To accompany this onboarding session, we created a set of customizable illustrated instructions (see Figure 4) that walk participants through every step of the process, from turning on the recorder, placing it on the head of the child, to uploading the data. These instructions are intended to maximize participants' confidence in using the device, thereby, ensuring their successful compliance with study protocols. The data transfer workflow was designed to be as straightforward as possible for participants. We also created structured documentation for troubleshooting common technical issues and addressing frequently asked questions; all instructions, documentation, and onboarding materials are available at https://osf.io/kwvxu/, and a brief overview can be found at https://langcog.github.io/babyview/.

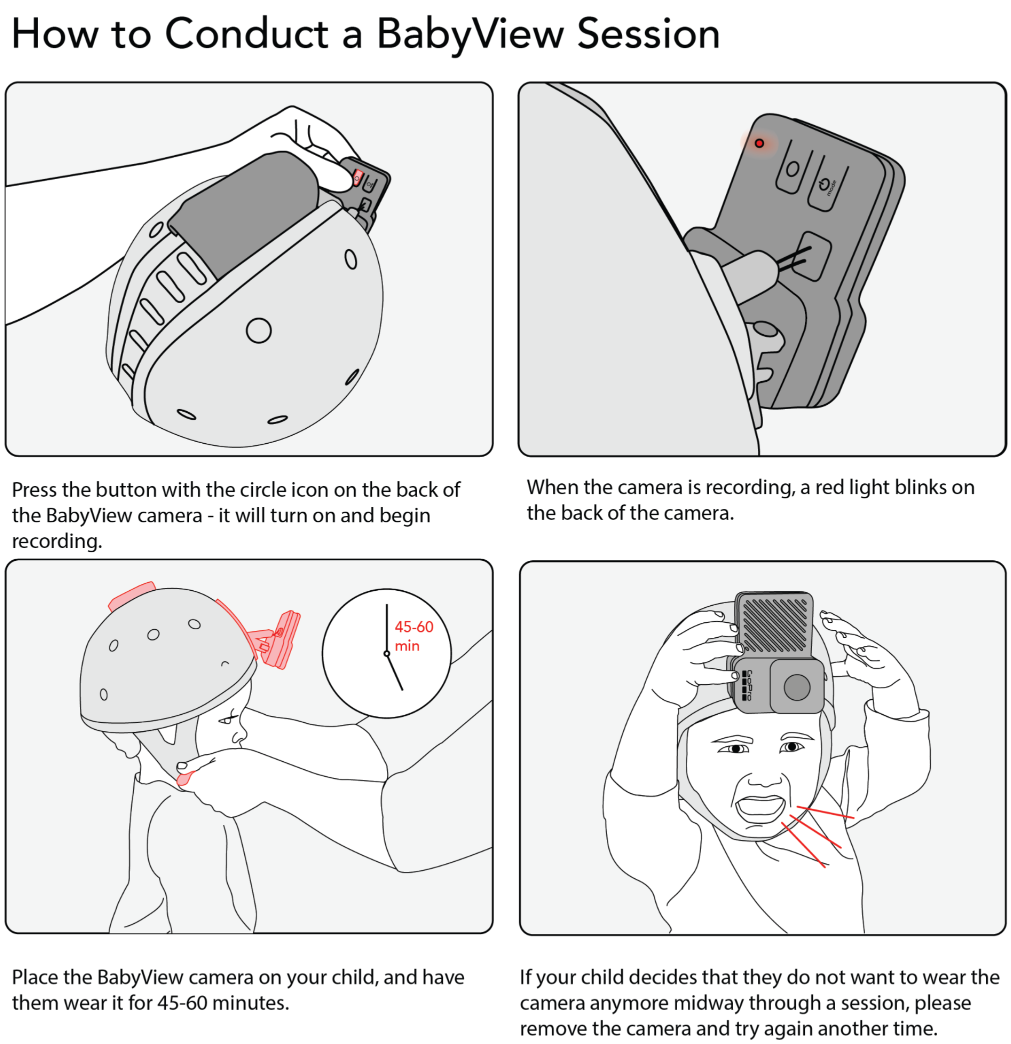

Figure 4. Schematic overview of instructions for running a BabyView session; these customizable Adobe PDF files are available on the OSF repository.

Participant privacy and consent for data sharing. We developed the following protocol to ensure participant consent and adequate privacy protections. During enrollment, caregivers are interviewed to determine which individuals are likely to engage with the child in the home.

All caregivers are asked to provide a blanket consent that will cover all current and future recordings. All caregivers can revoke their consent at any time. If any individual who engages regularly with the child chooses not to provide consent, participants are asked to record only when those individuals are not present. Participants are directed to stop recording at any time should the child become fussy or no longer wishes to wear the camera. If there are other children in the home besides the target child, any child eight years or older will be asked to provide oral assent at time of enrollment. In the case when a non-consented individual enters the home during a recording session, the caregiver is instructed to inform that individual of the in-progress recording and to ask for consent to be obtained at that time. If the individual declines, the caregiver is instructed to stop video recording or to delete the recording as soon as possible.

Participants are provided with a personal, password-protected cloud storage account through a PHI compliant, institutional secure Google Drive account. Videos can be uploaded from the camera to the account upon connecting a microSD card reader to their computer. Participants can also use their personal Google Drive link to access, upload, and review the video sessions via a website interface.

Participants have multiple opportunities to delete all or any portion of a recording. First, during the recording, a participant can use a voice command ("GoPro Highlight") to highlight a sensitive moment in a video, and then a period of time around that video can be deleted automatically after upload in the data preprocessing pipeline (e.g., a 4 minute window consisting of 2 minutes prior and 2 minutes after the voice command was issued). Second, the participant can remove the video directly from their personal cloud storage account prior to those videos being uploaded. Third, the caregiver can indicate in a follow-up survey that any or all of a particular video should be deleted. Finally, the participant can email the research team directly and ask that the video be deleted. These actions are all available to the participant up until the videos have been deposited into a data shared repository (e.g., Amazon S3 storage), typically, 6 months after the initial recording (see Data management workflow).

Data management workflow

Participants are given instructions to plug in the microSD card to their computer via a USB connection (provided with the BabyView); we link instructions for the participant on the microSD card to ensure as smooth of a process as possible. Participants click a link on the microSD card which opens their personalized Google Drive folder in a web browser, and then can drag the videos from the microSD card file manager into the "upload" window on their Google Drive account. Participants will then be instructed to delete the videos on the microSD card via this same interface once every two weeks, which should be sufficient given the large data capacity of these new cards (256G).

Once videos have been uploaded to Google Drive, our data management pipeline consists of the following four steps: 1) automatically downloading the videos; 2) extracting the metadata that are needed for analysis; 3) compressing the videos so that they occupy much less space than the original videos; and 4) uploading the compressed videos and the corresponding metadata to cloud drives (i.e. Amazon S3 buckets) for permanent storage. In our implementation, this pipeline is run weekly to distribute the burden on network and computation. Code for this pipeline is publicly available at https://github.com/neuroailab/BabyViewPublic.

The downloading steps is implemented through programmatically interacting with the Google Drive servers. The extracted video metadata include both the timestamps when a voice-or button-controlled highlight is detected and extra sensor signals like the camera's accelerometer and gyroscope. All metadata are extracted directly from the video file according to the structured storage format defined by GoPro; this extraction process makes use of a data parser distributed by GoPro (https://github.com/gopro/gpmf-parser). The compression step uses the program "ffmpeg" (Tomar, 2006) to encode the videos into "libx265" format, which produces high quality videos in .MP4 format.

Pilot Study

To test the usability of the BabyView, we conducted iterative piloting sessions throughout device development stages and with different prototypes. A first set of 6 infants (aged 8, 9, 15, 16, 26, 36 months) were recruited to test the wearability of a helmet-based recording device while a team member was present, without attempting to use the cloud storage interface and pipeline. After the beta build was complete, a second set of families were shipped devices to their homes and asked to record on their own. Families were onboarded via Zoom and e-mail. We debriefed these experiences with each family via a combination of surveys and as well as qualitative interviews.

Pilot wearability. Overall, we found that children generally tolerated the BabyView camera well, and that the camera stayed in place once adjusted on the child's head. A final version of the camera now includes an additional adjustment strap on the back of the helmet which allows the helmet size to be customized for each child, particularly for younger children with smaller head sizes. Children who disliked wearing hats in general were less likely to tolerate wearing the BabyView; conversely, older toddlers who were used to wearing helmets seemed relatively unbothered by the device and wore it without much convincing. In general, babies were relatively content to wear the cameras for 20-90 minutes. In the subset of families that had the camera for an extended period of time, some families opted to conduct multiple, short sessions (e.g., three 20-minute sessions) with their infants, whereas other families conducted a single longer session. Some families reported that subsequent sessions were easier than initial sessions when their child was first introduced to the device. However, these pilot sessions did reveal that the BabyView may be unsuitable for younger infants who tend to spend the majority of their time laying on their backs while playing, as the helmet can sometimes slide forward when a child lays down. Thus, the BabyView may be best suited for children who are able to sit up unassisted and, as in prior work, who do not have a strong aversion to wearing hats.

Figure 5. Example images and off-the-shelf Mask-R CNN segmentations (confidence > .3) on frames from the BabyView camera. These higher-resolution egocentric images provide better data for segmentation than previous cameras, yet are still quite challenging for state-of-the-art models.

Pilot data analysis. We anticipated that the BabyView's higher-resolution images would result in better object segmentation and detection performance than in previous work. Figure 5 shows object detection performance from a Tensorflow[2] implementation of Mask R-CNN ((He et al., 2017) on two example frames from the BabyView. Overall, we found that off-the-shelf object segmentation models benefitted considerably from the extra resolution provided by the BabyView —though these egocentric, child-centric images remain challenging for computer vision models trained on images taken from the adult perspective.

Adopting the BabyView

Our goal in creating the BabyView was to provide an openly-available head-mounted camera design for infants, in the hopes of encouraging broad adoption of the device and thus decreasing the costs associated with beginning developmental research using egocentric video. Our schematics are openly available at https://osf.io/kwvxu/ and they contain detailed specifications including: (1) purchasing links and model numbers for components, (2) design files for the 3D printed camera attachments, (3) step-by-step instructions for assembly of the GoPro and attachment to the helmet, and (4) further instructions for configuration of the camera and microSD card. We were able to assemble a BabyView ourselves in about 30 minutes with an accessible set of commercially available tools (e.g., heat gun, soldering kit, pliers).

One major concern for scientific devices that draw on the commercial ecosystem is their continued future availability. In particular, our design is predicated on the GoPro Hero Bones camera and its specific physical configuration and functionality. Several factors contributed to our selection of this camera. First, this camera is widely available through standard purchase channels. In addition, GoPro has an extensive user support community accessible on their

[2] Using codebase at https://github.com/tensorflow/tpu/tree/master/models/official/mask_rcnn

product website as well as other non-affiliated sites. Finally, the Hero Bones model was released just a few months prior to its adoption in this project. Although it is possible that the camera may be discontinued in the next few years, we anticipate that units should continue to be available for at least several years. Further, because the battery in our design is external to the camera and easily replaceable, battery degradation in second-hand or older hardware should not be an issue. Thus, we expect that our exact design should remain usable for years to come.

Our design is also extensible and modifiable. There are a number of scenarios in which end-users might wish to modify the design. First, in the case that a new camera unit with substantially better functionality is released, the 3D printed mounting could be modified to accommodate camera hardware with slightly different dimensions or screen positioning. This modification would require some design expertise but should not be prohibitively difficult. Second, the design could be adapted for use with other populations (e.g., school-aged children) or enclosures. For example, identification and modification of a differently sized helmet is likely possible.[3]

Discussion

In this paper, we have presented BabyView, a new custom egocentric camera design suitable for use with infants and young children. The BabyView is designed to collect high-resolution, wide-field egocentric video and associated metadata— including gyroscope and accelerometer data—from children via a safe and comfortable wearable device. One of our primary goals was to be able to capture children's home experiences, and so we also presented a data collection and data management workflow for efficient and privacy-preserving use of the

[3] For adults and older children, the BabyView camera enclosure is unnecessary and the easiest possible solution might simply be to use a GoPro 10 or other model and a standard action sports helmet with GoPro mounting; such helmets are commercially available at low cost.

BabyView in families' homes. Our pilot data show that data collection of this type is possible, though—as with previous designs—convincing toddlers to wear a head-mounted device remains challenging.

More broadly, egocentric video has tremendous promise for yielding insights into children's development, both through descriptions of their learning environment and inputs to computational learning systems. Yet progress towards these goals has been slower than expected, in part due to a paucity of comparable data representing the experiences of a diverse range of children. By creating an openly available device, we hope to encourage adoption of similar recording methods across laboratories and populations. Importantly, the use of standardized methods can lead to more comparable measurements across different research projects. For example, if multiple laboratories measure children's access to faces, these measurements will be more easily comparable if the cameras have the same field of view.

Our hope is that the higher quality of data collected by the BabyView (as compared with previous datasets, e.g., SAYCam; Sullivan et al., 2020) may lead to new opportunities to understand the regularities in children's everyday learning environments and how they are related to learning. More specifically, studies of head motion and visual attention might benefit from the availability of accelerometer data (Borjon et al., 2021), and studies of the availability of social information will likely benefit from the wider field of view (cf. Fausey et al., 2016; Long et al., 2022a, 2022b). Further afield, the higher resolution, better audio, wider distribution, easier-to-use cameras, and the collection of larger data-sets enabled by the BabyView might also make new algorithms from computer vision testable on developmental egocentric data (Feichtenhofer et al., 2021; Morgado et al., 2021). More broadly, we hope that the availability of higher-quality information about children's visual experience leads to new insights about development.

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References

Aslin, R. N. (2009). How infants view natural scenes gathered from a head-mounted camera. *Optometry and Vision Science: Official Publication of the American Academy of Optometry*, *86*(6), 561–565.

Bergelson, E., & Aslin, R. N. (2017). Nature and origins of the lexicon in 6-mo-olds. *Proceedings of the National Academy of Sciences*, *114*(49), 12916–12921.

Borjon, J. I., Abney, D. H., Yu, C., & Smith, L. B. (2021). Head and eyes: Looking behavior in 12-to 24-month-old infants. *Journal of Vision*, *21*(8), 18–18.

Clerkin, E. M., Hart, E., Rehg, J. M., Yu, C., & Smith, L. B. (2017). Real-world visual statistics and infants' first-learned object names. *Phil. Trans. R. Soc. B*, *372*(1711), 20160055.

Fausey, C. M., Jayaraman, S., & Smith, L. B. (2016). From faces to hands: Changing visual input in the first two years. *Cognition*, *152*, 101–107.

Feichtenhofer, C., Fan, H., Xiong, B., Girshick, R., & He, K. (2021). A large-scale study on unsupervised spatiotemporal representation learning. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 3299–3309.

Forster, C., Carlone, L., Dellaert, F., & Scaramuzza, D. (2016). On-manifold preintegration for real-time visual–inertial odometry. *IEEE Transactions on Robotics*, *33*(1), 1–21.

Franchak, J. M., Kretch, K. S., & Adolph, K. E. (2017). See and be seen: Infant–caregiver social looking during locomotor free play. *Developmental Science*.

Franchak, J. M., Kretch, K. S., Soska, K. C., & Adolph, K. E. (2011). Head-mounted eye tracking: A new method to describe infant looking. *Child Development*, *82*(6), 1738–1750.

He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask R-CNN. *Proceedings of the IEEE International Conference on Computer Vision*, 2961–2969.

Kretch, K. S., Franchak, J. M., & Adolph, K. E. (2014). Crawling and walking infants see the world differently. *Child Development*, *85*(4), 1503–1518.

Long, B., Kachergis, G., Agrawal, K., & Frank, M. C. (2022). A longitudinal analysis of the social information in infants' naturalistic visual experience using automated detections. *Developmental Psychology*. https://doi.org/10.1037/dev0001414

Long, B., Sanchez, A., Agrawal, K., Kraus, A. M., & Frank, M. C. (2022). Automated detections reveal the social information in the changing infant view. *Child Development*, *93*(1), 01-116.

Morgado, P., Vasconcelos, N., & Misra, I. (2021). Audio-visual instance discrimination with cross-modal agreement. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 12475–12486.

Nagarajan, T., & Grauman, K. (2021). Shaping embodied agent behavior with activity-context priors from egocentric video. *Advances in Neural Information Processing Systems*, *34*.

Orhan, E., Gupta, V., & Lake, B. M. (2020). Self-supervised learning through the eyes of a child. *Advances in Neural Information Processing Systems*, *33*, 9960–9971.

Smith, L. B., Yu, C., Yoshida, H., & Fausey, C. M. (2015). Contributions of head-mounted cameras to studying the visual environments of infants and young children. *Journal of Cognition and Development*, *16*(3), 407–419.

Sugden, N. A., Mohamed-Ali, M. I., & Moulson, M. C. (2014). I spy with my little eye: Typical, daily exposure to faces documented from a first-person infant perspective. *Developmental Psychobiology*, *56*(2), 249–261.

Sullivan, J., Mei, M., Perfors, A., Wojcik, E., & Frank, M. C. (2020). *SAYCam: A large, longitudinal audiovisual dataset recorded from the infants perspective*. https://psyarxiv.com/fy8zx/

Yoshida, H., & Smith, L. B. (2008). What's in View for Toddlers? Using a Head Camera to Study Visual Experience. *Infancy*, *13*(3), 229–248.

Zhuang, C., Yan, S., Nayebi, A., Schrimpf, M., Frank, M. C., DiCarlo, J. J., & Yamins, D. L. (2021). Unsupervised neural network models of the ventral visual stream. *Proceedings of the National Academy of Sciences*, *118*(3).