Synchronized Smartphone Video Recording System of Depth and RGB Image Frames with Sub-millisecond Precision

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Abstract—In this paper, we propose a recording system with high time synchronization (sync) precision which consists of heterogeneous sensors such as smartphone, depth camera, IMU, etc. Due to the general interest and mass adoption of smartphones, we include at least one of such devices into our system. This heterogeneous system requires a hybrid synchronization for the two different time authorities: smartphone and MCU, where we combine a hardware wired-based trigger sync with software sync. We evaluate our sync results on a custom and novel system mixing active infra-red depth with RGB camera. Our system achieves sub-millisecond precision of time sync. Moreover, our system exposes every RGB-depth image pair at the same time with this precision. We showcase a configuration in particular but the general principles behind our system could be replicated by other projects.

Index Terms—smartphone, synchronization, time synchronization, clock synchronization, depth camera, IMU, MCU, Android app, hardware synchronization, software synchronization, ROS, sensor network, recording platform

I. INTRODUCTION

The combination of complementary sensors generally produces a richer stream of data that is highly valuable for tasks related to robotics [1]–[3], sensor fusion [4], scene reconstruction [5]–[7] or data collection for training Deep Learning (DL) algorithms [8], [9]. For these tasks, the accuracy and precision of the timestamps from the different sensors can severely determine the quality of the obtained results, therefore our main concern is to ensure the maximum possible synchronization (sync) among all sensors in the recording system.

The particular aim of this paper is to study a system where at least one of the recording sensors is a smartphone. Data directly generated from smartphones are of great interest since many of the target applications will run directly on such devices. They also provide a complete suite of sensors, multiple cameras, IMU, and optionally depth, making them an ideal independent processing unit. However, they might need some support from external and higher quality sensors, for instance, to collect 3D-data from a depth camera. Is to this end that a smartphone RGB camera must be synchronized with the depth camera: a delay of only a few milliseconds might result in several pixels error.

The maturity of smartphone devices has significantly improved the camera quality over the last years, as well as their timestamping systems, driven by augmented reality (AR) application requirements. Unfortunately, they are closed systems that do not allow a direct wired trigger as in most industrial settings. Therefore, combining smartphone data requires hybrid hardware-software approaches to correctly sync the overall recording system.

In our first contribution, we propose a multi-modal heterogeneous hardware-software system for data collection. The system is based on MCU firmware for precise synchronization of 3D and RGB data from a camera and a smartphone, achieving sub-millisecond accuracy. At its core, our approach is a continuation of our previous algorithm proposed in [10] for clock synchronization of heterogeneous systems of sensors by using gyroscope data and phase alignment of data at the application level, to guarantee precise triggering of the smartphone and MCU systems at shooting.

In our second contribution, we develop a mobile application for gathering smartphone sensor data with highly accurate and precise timing. This application, which combines electronics and software, has been made publicly available for the com-

This research is based on the work supported by Samsung Research, Samsung Electronics.

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Note that our platform provides two separate types of synchronization: (i) time synchronization – the entire obtained data are presented in a common time domain; (ii) frame synchronization – smartphone and depth camera frames are exposed at the same moments of time.

Our third contribution includes a customized evaluation of the precision between an active infra-red depth camera and an RGB camera. In this system, we are also able to measure the time drift of our system, which stays stable (<1ms) for more than 60 minutes.

The present paper is structured as follows: in Sec. II we review the related works, Sec. III overviews the main components of the recording systems and Sec. IV describes the sequence of programs and messages from the MCU, smartphone and mini PC. Sec. V-B describes the sync process between all the time authorities. Sec. VI evaluates the results and conclusions in Sec. VII close the paper.

II. RELATED WORK

Since our work lies in the intersection of multiple fields (data acquisition platform, synchronization, smartphone as a sensor), we briefly introduce current research related to our work.

HW platforms

Tschopp et al. [11] propose an open source sensor suite with HW triggering based on MCU. The system supports a number of sensors including visual, depth and inertial sensors. The authors achieve 1 ms sync accuracy and demonstrate sync importance on SLAM, mapping, navigation and reconstruction tasks. Liu et al. [12] share principles to follow for sensors sync and consider intra- and inter-machine sync levels. To realize the principles the authors design a FPGA-based platform for sync visual cameras, lidar, radar and IMU. For intra-machine sync they state 100 µs accuracy (lidar to the rest sensors). Nikolic and others [13] developed HW synced visual-inertial sensor unit for real-time SLAM based on FPGA. Due to tight integration inter-sensor time offset achieves down to several µs. Schuber et al. [4] present VI dataset and provide sensor description used for data gathering. The sensor is HW synchronized; however, time offset between the IMU and cameras is found by software sync using grid-search. Faizullin and colleagues [14] provide an open-source HW system design for IMU-to-lidar sync based on MCU. The system achieve 1 µs sync precision due to emulation of GPS clock by MCU in contrast to less precise PTP-based sync in [12]. Schneider et al. [15] propose a method for lidar to camera sync that makes visual camera expose images when lidar laser beam coincides with camera optical axis.

Network-based time sync

Interface for HW sensors sync is not always available. The main well-developed alternative approach to sync devices is to use network-based protocols. Those protocols are based on exchanging messages with time among devices in the sensor network and gathering statistics on arrival time between messages. The main representative of this class is NTP [16] protocol, supported on many OSes, including embedded devices. Among other protocols and algorithms Simple Network Time Protocol (SNTP) [17], Precision Time Protocol (PTP) [18], Reference Broadcast Synchronization (RBS) [19], and Lightweight Time Synchronization (LTS) [20] are worth to be mentioned since they provide sub-millisecond clock synchronization accuracy between devices. The main disadvantage of network-based protocols is the requirements on latency and symmetry of the network connection in order to perform fast and precise synchronization. Also, additional barrier of using network protocols is availability of protocol implementation on different platforms and the level of their control from the user side — i.e. in case of Android smartphones, despite the NTP daemon is provided on the platform, there is no flexible control on sync process from the Android API.

Data-driven time sync

Data-driven methods of sync are used as an alternative to the techniques above. Here we focus on methods of image frame sync from independent cameras that do not have common trigger and clock. A number of approaches to synchronize images are based on the analysis of common events captured by the cameras. Abrupt brightness change made by external light sources (natural or artificial) is a perfect companion for sync. Although need of the source, narrow down the usage of these techniques. Shrestha et al. [21] synchronize video recordings by detecting light intensity change of images produced by still camera flashes. This approach provides about 40 ms accuracy that is dictated by framing period. A simple though powerful method for synchronization of independent video streams with a precision better than one millisecond is proposed in [22]. There authors employ rolling-shutter effect of cameras to increase time resolution of external flashing events. Shrestha et al. [23] analyse audio track to synchronize independent video records of the same event and achieve sub-frame accuracy. Bradley et al. [24] set up external stroboscope to create common exposure for multiple rolling-shutter cameras. Thus, cameras receive photons avalanche reflected from the scene at the same period of time. This approach is useful in very controlled settings. In contrast to light-based methods, Caspi et al. [25] propose temporal-spatial matching of images from cameras by processing trajectories of moving object and obtain sub-frame synchronization accuracy.

Smartphone as a synchronized sensor

Since the quality of modern smartphones is being improved, these devices are becoming more popular as systems of sensors with a wide range of sensing modalities. They can provide more usage when coupled within a network. These types of networks need time sync, as well. There is a lot of research aimed at data synchronization from multiple smartphones. Callebaut et al. [26] consider smartphones as sensing platforms and sync them by GPS time data and NTP. Their sync performance analysis shows millisecond order accuracy and precision. Sandha et al. [27] carry out evaluation of smartphone-to-smartphone sync performance based on Bluetooth, Wi-Fi and audio peripheral and state (sub-)millisecond sync accuracy. Akiyama et al. [28] apply acoustic-light beacon for smartphone...
localization utilizing smartphone’s camera (rolling shutter effect) and microphone. Latimer et al. [29] – sub-frame video synchronization in a smartphone camera network based on NTP. Ansari et al. [30] propose Android app with their library for simultaneous photo shooting from multiple smartphones with sub-millisecond sync accuracy. They use custom NTP in local net with one smartphone as a server. In [10], the authors propose smartphones gyroscope based sync technique with microseconds accuracy. Smartphones must be rigidly attached for such high performance.

To the best of our knowledge, none of the existing platforms provide synchronization of heterogeneous sensors including smartphone and other sensors (RGB, depth camera, lidar, IMU, etc.). In contrast, our platform provides synchronous data gathering including smartphone video and depth camera images. Moreover, our technique allows sensors to be synced at sub-frame level providing tens of microseconds precision.

III. SYSTEM OVERVIEW

The system is designed to record smartphone videos synchronized at the time and frame level with depth images from an independent external depth camera. A common view of the system from the front and back sides is presented in Fig. 1. The main components of the recording system and their principal roles are as follows:

- **Smartphone** provides data from the camera (RGB) and built-in IMU (gyroscope, accelerometer, magnetometer).
- **Depth camera** provides high-quality depth data.
- **Standalone IMU** provides gyroscope necessary for synchronization algorithm [10] between smartphone and depth camera data. Accelerometer data are also available.
- **MCU** acts as hardware level mediator: obtains standalone IMU measurements, controls triggering of the depth camera, and collects essential metadata.
- **Mini PC** controls all the recording process, that includes interaction with the smartphone, depth camera and MCU.

All the system components are mounted on the handheld plywood platform designed to carry them comfortably during recordings in the way presented in Fig. 2. A metal rig strengthens the platform body to have constant relative transformations between every sensor. The system is battery-powered and can work several hours after full charge.

An additional laptop allows the operator to easily control the recording process via an SSH connection. During the recording, the smartphone data is saved on the smartphone, whereas other data (depth, inertial data) is saved on the mini PC. Once the recording finishes, all data are transferred to a common machine, where post-processing re-assigns timestamps into a common time reference.

A. System topology

The block scheme of the system is drawn in Fig. 3, and it shows the components’ connections and data flow between them. The depth camera and standalone IMU (through the MCU platform) are connected to the mini PC via a USB interface. The smartphone is connected to the mini PC via a Wi-Fi network, using an access point launched on this PC. Communication between smartphone and mini PC is performed using remote API that provides the application “OpenCamera Sensors” [31] that runs on the smartphone. This API allows to run and stop video and IMU recording over the network commands. The depth camera is additionally connected to the MCU platform for synchronized frame triggering.

B. Hardware specifics

In our system configuration, we use the Samsung S10e smartphone, Azure Kinect DK depth camera (other sensors besides depth are not used), standalone MPU-9150 IMU-sensor, NUC mini PC, powered by Ubuntu 18.04 OS, Intel(R) Core(TM) i7-10710U CPU @ 6-Core 1.1GHz, 16 GB DDR4-2666MHz RAM., 500 GB M.2 SSD storage, STM32F4DISCOVERY MCU platform based on STM32F407 MCU. The smartphone is powered by Android 10 OS and utilizes a standard camera for video recording with 1920x1080 pixel resolution and a 30 fps frame rate. The smartphone IMU sensor (gyroscope, accelerometer) collects inertial measurements at 500 Hz data rate. The standalone IMU has the same sensor types and the same data rate. The depth camera is set up to shoot depth images with narrow field of view with 640x576 pixel resolution and a 5 fps frame rate.

IV. SYSTEM SOFTWARE

For our system, we have developed the next software components: (i) smartphone application, (ii) MCU firmware, (iii) mini PC and (iv) data extraction software. The first three components are used in the recording process, the last one is employed in the post-processing step.
Fig. 3. The system topology. Arrows show data/command directions. The depth camera and MCU-platform are connected to the PC via USB connection, the smartphone and the laptop are connected to the Wi-Fi network launched on the PC.

A. Smartphone application

For recording smartphone data and providing communication between the smartphone and the rest of the system, we developed the Android application OpenCamera Sensors, publicly available at GitHub [32]. It is based on the open-source application OpenCamera [31] that provides flexible control of camera parameters. OpenCamera Sensors extends it with a synchronized recording of the camera and IMU data, as well as provides remote control over the Wi-Fi network.

The next main features of the OpenCamera Sensors are used in the recording pipeline: (1) start/stop recording video and IMU data — for data collection, (2) start/stop IMU recording and return recorded data as a response — for gyro-based time sync, (3) provide information about phase and period of video at the beginning of the recording — for frame sync. By phase, we name relative offset between frames middle points exposure moments of neighboring smartphone and depth camera frames. By definition, the absolute value of the phase cannot exceed the framing period of the sensors.

The recording process has the following specific properties, which are needed for minimization of smartphone post-processing effects.

1) For constant cameras extrinsic relation, we disable video stabilization
2) Turning off sound recording is necessary to avoid the addition of extra frames by Camera2API software.
3) We lock exposure to achieve a constant frame rate, as auto exposure can produce "leaps" in frames when exposure changes.

B. MCU

MCU platform is used to perform several tasks aimed at synchronization and recording: (i) gathers timestamped inertial data from standalone IMU — for MCU to smartphone time synchronization, (ii) triggers depth camera frames — to synchronize them at the frame level with smartphone RGB-camera frames, (iii) collects and sends meta-information — for final stages of synchronization during data extraction. IMU data gathering process is described in [14]. The depth camera triggering is available because the sensor has a dedicated HW interface for this process. MCU platform provides the triggering pulses with a specific phase to the interface for frames sync with the smartphone camera. Its usage is discussed in more details in Sec. V-D.

C. Mini PC

Mini PC software consists of two main parts — synchronization and recording. During the synchronization process, it interacts with the smartphone (over remote control API) and MCU to perform time and frame-level sync between the smartphone camera and depth camera, as it will be described in detail in Sec. V-D. During the recording process, the software running on the mini PC presents multiple ROS nodes that collect data from the sensors associated with mini PC — depth camera, standalone IMU, and meta-data for post-processing. We improved the depth camera driver to gather images with depth camera internal timestamps instead of ROS timestamps. This modification allows sync to avoid intermediate ROS time. MCU-IMU driver is entirely developed from scratch and is also available on the project page. Collected data are saved to a common rosbag file.

D. Data extraction software

When data collection is finished, corresponding files are manually uploaded from the smartphone and mini PC to the external machine. Using software for data extraction, they are unpacked and assigned with timestamps in common time reference. During the extraction, all timestamps are transformed to a single time domain. The tool puts all the extracted files into sub-directories, named after corresponding topics. The extractor uses rosbag API to extract messages from the required ROS topics and ffmpeg for smartphone images extraction.

V. SYNCHRONIZATION

The collected data from the sensors has small value if the sensors do not have a common time reference. In order to get a common time reference, time sync must be performed among available sensors, which in our case are smartphone and depth camera. Because the frame rate of both sensors is low enough (30 fps and less), the naive calculation of the time difference between frames captured could achieve up to 16.7 ms. This delay could be crucial when capturing dynamic scenes or when the platform is moving (rotating) during the capture. To overcome this, frame sync also should be performed between smartphone frames and depth frames. This section describes both subtasks and how they are reflected in the design of our system.
A. Clock reference

To perform time sync, a common clock reference should be chosen. Our system has three different clock sources — mini PC, smartphone, and MCU. The mini PC clock is not suitable for reference due to its loose relation to the other two clocks: neither the MCU nor the smartphone have a precise sync technique to the mini PC clock. Moreover, the mini PC does not have a precise timestamping procedure for the sensors connected to it (depth camera, standalone IMU). Both the MCU clock and the smartphone clock could be chosen as a reference clock, to which every measurement is synchronized. In our work, we use the MCU-based clock for its certainty.

B. Time sync

A direct wired-time sync of system’s components is not available because smartphones do not allow for such an interface. Common network-based protocols for time sync, such as NTP [16] or PTP [18], are also not suitable candidates for our system due to: (1) they rely on network symmetry and constant latency, which neither PC nor the smartphone guarantee due to uncontrollable background network operations, (2) absence of flexible operation with NTP/PTP daemons on the smartphone.

In order to solve this hindrance, we use time synchronization by shaking the rigidly attached sensor rig, and thus, creating a common IMU signal to process the relative time offset by our twist-n-sync algorithm [10].

C. Frame sync

The canonical way of synchronizing data on the frame level is to use hardware triggering of target devices. In our case, the smartphone doesn’t provide such an interface, whereas the depth camera supports it. Therefore, to synchronize devices on the frame-level, we use the following approach that avoids a wired triggering:

1) The smartphone starts video recording and shares phase parameters of the current video recording with a mini PC over the application Wi-Fi interface.
2) Taking into account information about the smartphone phase, mini PC adjusts phase of the depth sensor using hardware triggering via MCU.

This approach requires both smartphone and depth camera to have a constant frame rate. On the smartphone, this property is guaranteed by blocked exposure, on depth camera – by hardware triggering with constant period. Moreover, the frame rates must be equal or multiple of each other to keep frame alignment over time.

D. Recording pipeline with synchronization

This section describes the overall recording pipeline and implementation details that provide synchronized data from the smartphone and depth camera on frame level.

The recorder communicates with the smartphone through the application described above (in Sec. IV-A). When the app is launched, the recorder checks the network connection with it. Then the recorder launches depth camera [33] and MCU through their ROS drivers. We modified the depth camera driver for its correct timestamping. After the sensors are launched, MCU starts to trigger depth camera frames and provides their timestamps in the MCU time domain. The recorder catches the first triggered timestamp in the MCU and smartphone time domains to obtain and publish the time offset between these two timestamps:

$$\Delta t_{DM} = t_{D_0}^D - t_{D_0}^M,$$

where $t_{D_0}^D$ and $t_{D_0}^M$ denote the time of the initial depth frame shot $D_0$ in the depth and the MCU time domains respectively.

Then smartphone-to-MCU time synchronization is performed to obtain the time offset between their clocks using gyrooscope-based time sync algorithm [10]. During this step, the whole system is hand-twisted to generate shake events. The obtained offset is:

$$\Delta t_{SM} = t_{S_0}^S - t_{S_0}^M,$$

where $t_{S_0}^S$ and $t_{S_0}^M$ are time of the initial smartphone frame shot $S_0$ in the smartphone and MCU time domains respectively. The offset obtained by the method is then published to its ROS topic for further use in data alignment during extraction.

The next step is frame alignment between smartphone camera and depth camera. The alignment happens after the start of smartphone video recording, because at that moment a constant period is guaranteed [34]. Accordingly, the smartphone time $t_{S0}^M$ and depth camera time $t_{D0}^M$ have been estimated and are now expressed in the same reference frame $M$, the MCU clock domain. We remove the frame superscript for clarity. Under the assumption that the smartphone and depth camera framing periods are constant, the exposure moments can be expressed by:

$$t_{Sn} = t_{S0} + Tn,$$
$$t_{Dm} = t_{D0} + Tm + \Delta t_{phase},$$

where $T$ is the framing period, $n$ and $m$ are frame counts, $\Delta t_{phase}$ is the phase shift that has to be set up for frame alignment, initially it equals zero. The smartphone and the depth camera are considered aligned if $t_{Sn} = t_{Dm}$ for some pair $(n, m)$; then $\Delta t_{phase}$ for frame alignment can be found by:

$$\Delta t_{phase} = t_{S_n} - t_{D_m} \pmod T,$$

$$= t_{S_0} - t_{D_0} \pmod T.$$
The obtained $\Delta t_{phase}$ is sent to the MCU that finally corrects the phase on the fly. At this stage, smartphone-to-depth camera frame sync is completed.

MCU HW can set up the phase with a discrete step size equal to about 390 ns that is negligible to the overall precision of the sync that is discussed in the next section.

After obtaining offsets and performing frame sync, the system is ready for recording, which could be initiated by pressing a button on monitor laptop by the operator. During the recording, all needed data threads are captured into a single ROS bag file. The smartphone records the data into its flash memory. After recording, the system is stopped by the operator.

VI. EVALUATION

In this section, we evaluate precision of the frame sync and accuracy drift over time. As we mentioned in related work, previous works [10], [22], [30] utilize controlled light sources for evaluation of the sync performance of their methods. The light sources emit short light flashes or strobes in specific time moments. The strobes are then caught by cameras (two smartphone cameras, etc.) and the analysis of the synchronized images is performed. Due to a rolling shutter effect, the strobes are visible only on some rows of images that are exposed at this moment. By row position difference between the synced images, one can estimate accuracy and precision of sync. For this analysis, row readout time must be known for every image sensor to transform row position difference to time duration.

We have proposed a variation of the above principle in order to measure depth-RBG time alignment. Our controlled light source is a depth camera projector that provides infrared (IR) strobes of light. The strobes are normally used by Azure Kinect DK as a light source in the depth estimation process. The projector generates the strobe train of 9 strobes at every frame sync. Below, we show inter-launch sync precision. This means we monitor row position at every recording start for a number of system launches. As a result, the obtained row position distribution provides a precision measure.

However, IR strobes are invisible to the smartphone camera image sensor because of IR-filter in the camera optical scheme. To bypass this issue, we designed a light re-transmitter that receives the IR strobes and repeats them in the visible spectrum. The visible light is then captured by the smartphone camera with no constraints. Common view of the re-transmitter and experimental setup are shown in Fig. 5. Re-transmitter transforms IR-light to electrical signal by photo diode, then amplifies the signal power to flash LED-strip.

To collect the inter-launch row positions, we recorded 52 short smartphone video sequences and extracted 16 consequent frames from every video, see Fig. 6. For each of these frames from a single video we obtained per-row intensity and by averaging the intensities we calculated aggregated per-row intensity to get more robust peak positions. To achieve this, we smoothed the peak positions with a Gaussian kernel applied to the per-row intensity curve (kernel size is 7 lines or 71.4 $\mu s$). After smoothing, we choose the area that includes certain peak for every frame in every recording (fourth peak is chosen as the highest peak among the others) and obtained the peak position for every trial curve. This peak distribution measure the precision, listed in Table I. The row-to-time transformation was obtained by measuring inter-peak row quantity knowing the time between peaks from [33]. During evaluation recordings, we manually injected several millisecond delay of depth camera phase to always observe the first strobe on the smartphone images. This is to be sure that the fourth peak is picked up on every image. Otherwise, it is not possible to enumerate strobes because the whole train does not fit into an image (this can be seen in Fig. 5).

For drift evaluation, we recorded a 5-minute video and gathered the row position for every sixth frame. Then linear regression is applied to 2100 pairs (frame timestamp – row position) to take frame sync drift over time (Fig. 7). The result is in Table I.

We do not provide accuracy value of system sync because relative delay between smartphone and depth camera exposure starts is set up manually to see the fifth strobe in the middle of smartphone images.

| Table I | Synchronization precision and drift |
|---------|-----------------------------------|
| IQR(SD) | 66.3 (61.6) $\mu s$                |
| Drift   | 16.34 $\mu s$/m                    |

VII. CONCLUSION

In this paper, we have proposed a recording system of heterogeneous sensors including, but not limited to Azure depth camera, IMU and smartphone camera. The main contribution of our work is on the hybrid approach to synchronize different time authorities: MCU and smartphone in our case, but easily extendable to other configurations. To achieve this, we have combined traditional wired-based trigger sync with software sync for the smartphone.

In addition, we have develop a data collection system using smartphone data with highly accurate and precise timing. We have shown that our system achieves a precision of 66 $\mu s$ and maintains stable sync conditions for recording during several minutes. In addition, we have proposed a new measurement process to establish synchronization between an active infrared emitter and an RGB camera (smartphone), customized for the platform requirements. All code, design and scripts necessary to replicate our recording platform or modify it with new configurations, have been made publicly available.

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Fig. 5. Common view of the re-transmitter (left) and experimental setup (right). The amplifier is used to strengthen the photo diode signal to flash LED-strip. The smartphone camera is set up to the lowest exposure time to resolve the train of short strobes. This is seen that no more than five strobes can be observable on the single smartphone image because whole image readout time is less than the strobes train duration.

Fig. 6. Statistic gathering for frame sync precision evaluation. Row position determination is shown for a single record from 52 in total. The number of frames for the determination is 16. The video frames images are corrected version of real ones in purpose of visualization.

Fig. 7. Frame sync drift estimation over 5 minutes. For clarity, the right axis indicates time scale of the drift.

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