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Wireless inertial measurement unit with GPS (WIMU-GPS) – Wearable monitoring platform for ecological assessment of lifespace and mobility in aging and disease

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Abstract—**This paper proposes an innovative ambulatory mobility and activity monitoring approach based on a wearable datalogging platform that combines inertial sensing with GPS tracking to assess the lifespace and mobility profile of individuals in their home and community environments. The components, I/O architecture, sensors and functions of the WIMU-GPS are presented. Outcome variables that can be measured with it are described and illustrated. Data on the power usage, operating autonomy of the WIMU-GPS and the GPS tracking performances and time to first fix of the unit are presented. The study of lifespace and mobility with the WIMU-GPS can potentially provide unique insights into intrapersonal and environmental factors contributing to mobility restriction. On-going studies are underway to establish the validity and reliability of the WIMU-GPS in characterizing the lifespace and mobility profile of older adults.**

I. INTRODUCTION

In older adults over 65 years of age, the prevalence of impaired mobility varies between 7.7% and 35% [1]. Mobility is broadly defined as the ability to move oneself (e.g., by walking, by using assistive devices, or by using transportation) within community environments that expand from one's home, to the neighborhood, and to regions beyond [2]. It is also a fundamental part of self-care activities and instrumental activities of daily living (ex; meal preparation, homemaking, shopping, leisure) within an individual's place of residence or the community. Normal aging is associated with declines and deficits in a number of physiological systems that are essential for mobility: balance, strength, sensory detection and integration, motor coordination and cognitive processing. These declines can be accelerated by musculo-skeletal and neurological diseases such as osteoarthritis, stroke, Alzheimer's and Parkinson's (PD) as well as by the effects of injury. Preserving mobility has now become a critical part of maintaining function and preventing further disability in older adults and adults with disease [3]. Understanding the determinants of mobility disability is essential in developing interventions aimed at preserving mobility in older adults.

The determinants of mobility disability have traditionally been studied using outcomes from laboratory (motion analysis), clinical (observational) and community (self-report) approaches. Overall, these approaches have trade-offs in terms of precision/accuracy, validity/reliability, time/cost, training/expertise, participant burden and real-world generalization and are often just a proxy for the mobility of the individual, as they fail to capture the dynamics between the environment, the intrapersonal factors of mobility restriction and the real life expression of this mobility [4]. With the advent of miniaturized body-worn sensing technology, it is now possible to collect and store data on different aspects of human movement and mobility under free-living conditions over long periods of time. For example, over the last 10 years, inertial sensing of motion has proven to be a suitable alternative to traditional image-based motion analysis systems in several clinical applications [5]. Advances in geotracking (Global Positioning System-GPS) and geocoding (Geographic information system-GIS) methods have allowed health researchers to efficiently track and model behaviors such as out-of-home mobility in the time-space domain and measure access to built-environment resources and exposure to social problems or risks [6].

In this paper we propose an innovative mobility and activity monitoring approach based on wearable inertial sensors with GPS tracking, data logging capabilities and an external mobility sensor interface, to study the determinants of ecological mobility in aging and disease. At the core of this approach is an activity-monitoring platform called Wireless Inertial Measurement Unit with GPS (WIMU-GPS). The first part of the paper describes the architecture of

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the system and its components. The second part illustrates outcome variables used to assess lifespace and activity of individuals. The third part presents performance data obtained in the preliminary validation of the platform.

II. WIMU-GPS PLATFORM AND DATA ARCHITECTURE

The WIMU-GPS consists of a datalogger with embedded sensors and I/Os that can be connected to external sensors (Figure 1). The dimensions of the platform are: 4.5 cm (width) by 7.2 cm (length) with a 1.6 cm thickness.

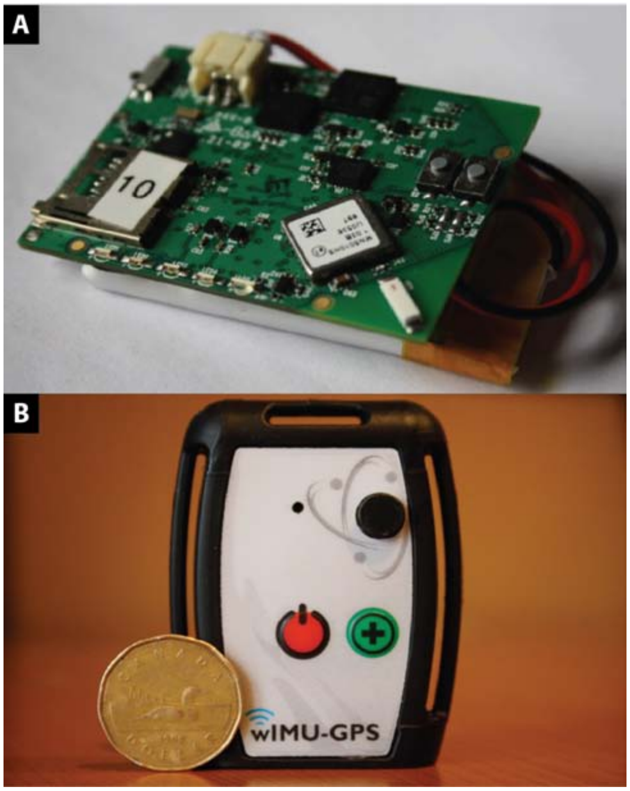


Figure 1. Overview of WIMU-GPS platform a) Printed circuit board (PCB) with components and battery. B) Encapsulated PCB with face cover and controls.

The sensors and components embedded into the WIMU-GPS (Figure 2a) consist of the following: an inertial measurement unit (IMU), a GPS positioning device, a communication module (Zigbee and USB), a datalogging module on a microSD card and a power module (battery and charger). The IMU sensor consists of a triaxial accelerometer, a triaxial gyroscope and a triaxial magnetometer. Both the accelerometer and the gyroscope provide analog signals and are wired directly to the analog to digital converter (ADC) of the microcontroller. The magnetometer, also part of the IMU sensor is wired through the I^2C communication port of the microcontroller. These signals, amongst others, are recorded on a removable microSD card and later fed to a dedicated fusion algorithm based on an adaptive Kalman filter. These post-processing calculations enable pitch, roll and yaw angle measurements of the module. The SIRFstar III global positioning system (GPS) receiver provides the microcontroller with a digital datastream of user selected binary SIRF data including latitude, longitude, altitude and details about the satellite constellation seen by the unit. Data is sent through the Universal Asynchronous Receiver Transmitter (UART) port of the microcontroller. A second UART port enables USB communication with an external computer. Wireless communication can also be accomplished using the Zigbee communication module (connected using a Serial Peripheral Interface (SPI) port on the microcontroller). User interface is done using 2 push-buttons (WIMU On/Off and events marking) and five LEDs for status information. The heart of the circuit is an 18-megahertz low power 16-bit microprocessor with 256 Kb of flash memory and 16 Kb of RAM. All unused communication lines (both analog and digital) are routed to an external I/O connector providing further sensor connectivity.

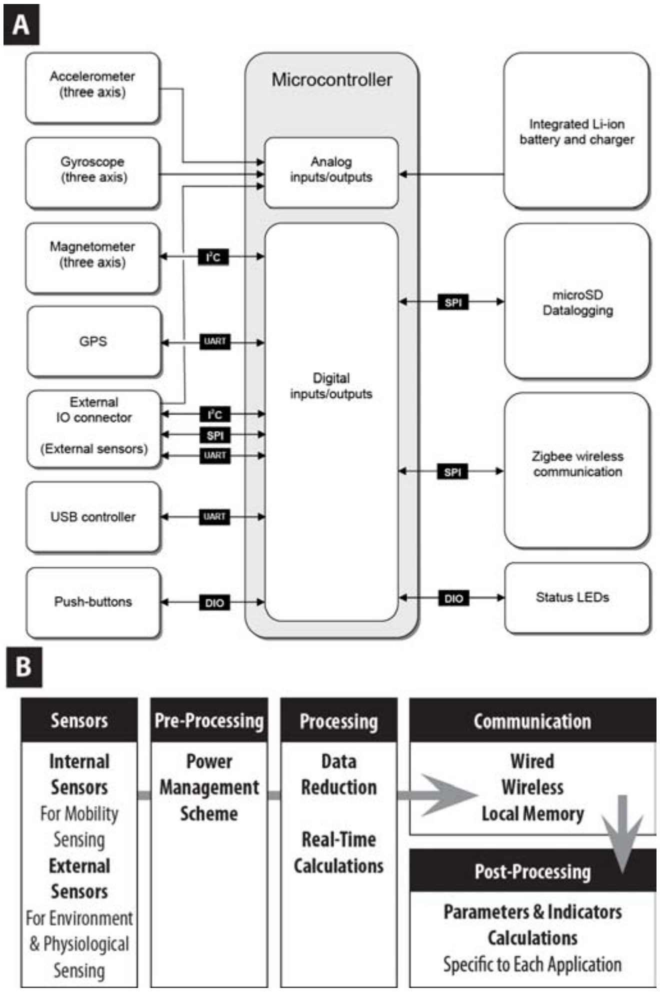


Figure 2. Overview of WIMU-GPS a) WIMU-GPS components and I/o architecture and b) data flow.

Data flow (Figure 2b) includes a pre-processing step that implements a power-management scheme required to provide long-term monitoring and recording of sensor data. The platform can be used to partially process the data on-board, reducing the size of that data and allowing real-time computations of variables. Besides logging the data in a local memory, the WIMU-GPS can also transmit all the collected data over a wired or wireless link. Using an external analysis software or system, data can be post-processed to generate variables of interest for the specific application the platform is used in.

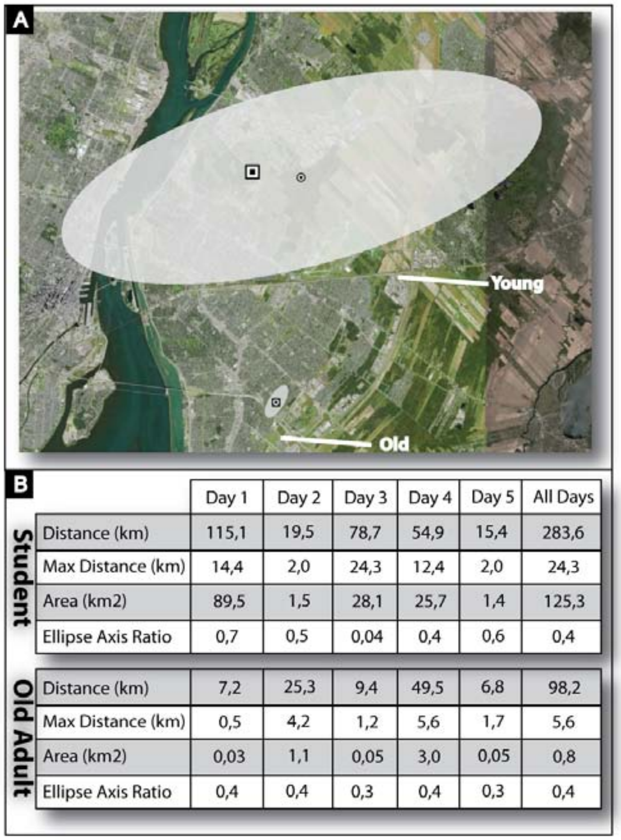
III. METHODS FOR LIFESPACE AND ACTIVITY ASSESSMENT

Figures 3 and 4 illustrate recordings from the 3D accelerometers and the GPS receiver on WIMU-GPS worn on the trunk by an older adult (female 71 years of age) and a university student (female 23 years of age) for 5 consecutive days. The following section describes the variables extracted from these recordings.

A. *Lifespace assessment*

In recent years, the measure of an individual's lifespace has been proposed as a better way to capture both the functional and psychological aspects of mobility while offering a better reflection of actual mobility performance [7]. Lifespace can be defined as the size of the spatial area a person purposely moves through in daily life, as well as the frequency of travel within a specific time frame [8]. The measure thus not only captures the actual spatial extent of movement but also the desire for movement and being involved in the larger social environment. The majority of previous research on lifespace assessment has been reliant on subjective self-report methodologies [9]. Innovations in GPS technology have opened the door to the development of portable and wearable GPS tracking devices that can be used to measure time-location data of human activity and assess the lifespace of an individual [10]. Using longitude and latitude data from the GPS receiver and a known reference point (the home), total area in km^2 of the mobility sphere (standard deviational ellipse of all geocoded data recorded), axis ratio of the mobility sphere, average of distances traveled per day during multiple days of recordings can be computed using spatial statistics [11, 12].

Figure 3 illustrates the lifespace determined from the 5 days of GPS recordings for the older adult and the university student. In figure 3A, individual ellipses show the area covered by the subject (including 95% of the GPS points) over the 5-days period. Squared dot indicates the subject's home while the circular dot indicates the mean center of the ellipse. In figure 3B, results over each of the 5- days and over all days are combined. Distance is the total distance moved by the subject. Max distance is the farthest distance from home the subject reached for the period. Area is the surface of the ellipse, a larger area expressing greater displacement coverage for the subject. Ellipse axis ratio is the ratio of the small and large axes. The closer the ratio to a "1" value, the closer the ellipse is to a perfect circle. Results clearly show that the lifespace of the older adult expressed as the surface of the ellipse over the 5 day period represent only about 0.6 % of the lifespace of the young subject.

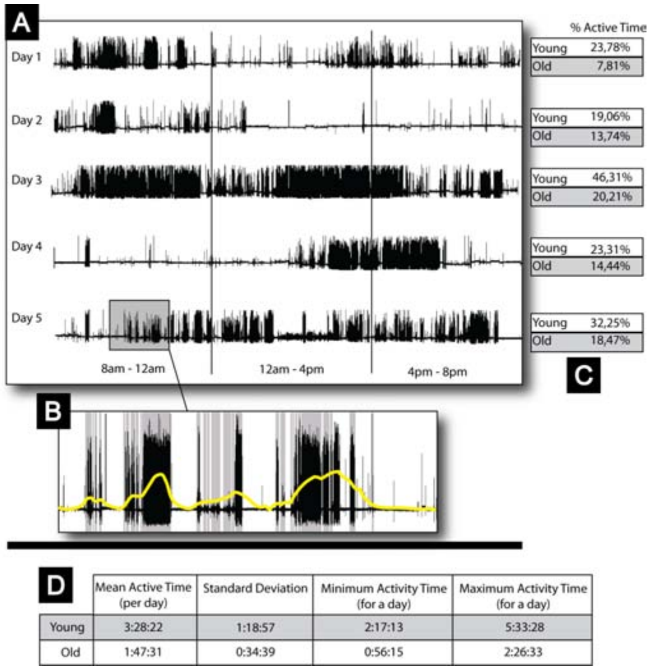


		Day 1	Day 2	Day 3	Day 4	Day 5	All Days
Student	Distance (km)	115,1	19,5	78,7	54,9	15,4	283,6
	Max Distance (km)	14,4	2,0	24,3	12,4	2,0	24,3
	Area (km2)	89,5	1,5	28,1	25,7	1,4	125,3
	Ellipse Axis Ratio	0,7	0,5	0,04	0,4	0,6	0,4
Old Adult	Distance (km)	7,2	25,3	9,4	49,5	6,8	98,2
	Max Distance (km)	0,5	4,2	1,2	5,6	1,7	5,6
	Area (km2)	0,03	1,1	0,05	3,0	0,05	0,8
	Ellipse Axis Ratio	0,4	0,4	0,3	0,4	0,3	0,4

Figure 3 Lifespace determined from 5 days of GPS recordings using the WIMU-GPS for an older adult and a university student.

B. *Activity assessment*

Accelerometry is often used to monitor mobility-related activities in older adults and people with different neurological and musculoskeletal conditions. Variables combining frequency and intensity of movement as well as orientation of body segments can be used to monitor a range of different movements, including gait, sit-to-stand transfers, postural sway and falls, to measure physical activity levels and to identify and classify movements performed by subjects [13]. In figure 4A, the amplitude of the acceleration vector (vector computed from each acceleration axis using $\sqrt{x^2 + y^2 + z^2}$) recorded in a 12-hour period over 5 consecutive days for the young subject is presented. In figure 4B, active time is calculated using the density of acceleration's peaks. Active time was estimated by extracting the temporal density of the acceleration signals. Raw signals from separate axes were combined, low-pass filtered (Butterworth, 1 Hz, 2^{nd} Order), rectified and high-pass filtered (Butterworth, 5 Hz, 2^{nd} Order). Data was then saturated in order to obtain a binary signal. Samples with a value above the noise baseline (15 mV), were considered as movements and were associated with a logic high state (ones). All other samples were set to a low state (zeros). A rectangular rolling window with a length of 10 seconds extracted the envelope of the binary signal and attenuated isolated peaks of acceleration, which were not related to physical activity, thus generating a signal with values varying between 0 and 1. Another threshold, optimized from previous recordings on a cohort of older adults, was fixed at 0.5. Every sample equal to or above 0.5 was considered as movement. The cumulative of these samples yielded an estimate of active time. In figure 4C, percentage of the time in a 12-hour day where the young and old subjects were considered to be active according to the calculation displayed in figure 4B. Cumulative statistics over the 5 days are shown in figure 4D. Results illustrate that the young subject was more active (about 50% more) than the old subject, as shown by the mean active time. The accuracy of this method was assessed by comparing time and motion measures during 62 real life physical therapy sessions with estimates of active time obtained with a 3D accelerometer module positioned at the hip of patients receiving treatments [14].



	Mean Active Time (per day)	Standard Deviation	Minimum Activity Time (for a day)	Maximum Activity Time (for a day)
Young	3:28:22	1:18:57	2:17:13	5:33:28
Old	1:47:31	0:34:39	0:56:15	2:26:33

Figure 4. Activity detection and active time calculation

IV. RESULTS

Design choices for the components used in the WIMU-GPS were made with the objectives of a) insuring a minimum monitoring time of at least 24 hours with the embedded sensors (i.e. IMU and GPS) under a motion based power management scheme b) reliable and accurate GPS tracking when worn on by the subject. Results of the power usage and performance of the GPS receiver when worn on the arm and trunk are described below.

A. Power usage of WIMU-GPS and operating autonomy

Table 1 shows the power (mW) drained by each individual component of the WIMU-GPS platform and its relative impact on the embedded 3700 mW battery. Power consumption was measured experimentally by shutting down and activating only a subsystem of the platform at once. Current measurement was done directly at the battery with an ampere-meter. As expected, the GPS subsystem and the Zigbee radio have the highest power requirement. Full on autonomy (with the Zigbee radio transmitting half of the time) is about 10 hours. Monitoring autonomy without the use of the radio is about 13,6 hours. Activity and mobility monitoring autonomy can be increased by using a motion based power management scheme that turns off the GPS when there is no activity, when the GPS is unable to acquire a position fix or when the GPS accuracy is too low to provide enough useful information. Tests are on-going to assess the best combination of parameters for the power management scheme. Under standby mode with power management on, the autonomy is about 99 hours.

TABLE 1. POWER USAGE OF WIMU-GPS AND OPERATING AUTONOMY

Module	Active Power (mW)	%
CPU	17.17	4.1 %
Accelerometers	20.16	4.8 %
Gyroscopes	41.2	9.8 %
Magnetometer	14.36	3.4 %
GPS	113.7	27.0 %
Zigbee (Stand-by)	44.9	10.7 %
Zigbee (RX-TX)	103.3	24.5 %
Datalogger (microSD)	66.1	15.7 %
TOTAL	420.9	100 %
Full-On Autonomy (h)*	10.0	
Monitoring Autonomy (h) **	13.6	
Motion Detection for power Management (h) ***	99.1	

* All systems on with no power management, radio at 50% TX;
** All systems on except radio and with no power management.
*** CPU and accelerometers on for power management scheme.

B. GPS tracking performances and time to first fix (TTFF).

To characterize the WIMU-GPS TTFF, it was compared to a commercial GPS data-logger (IGotU GT-120 from MobileAction). Both systems use a passive antenna and the same GPS chipset. A person wore both systems at two specific positions, arm and trunk, over a pre-defined trajectory (Figure 5). Data was collected over 10 different days to force the worst-case scenario: different satellite constellations requiring a full ephemeris download, also referred as a “cold start”. Figure 5 illustrates best (blue) and worst (red) TTFF position data for both GPS systems across 10 days. The test involved walking, following a defined path, stopping for a minute in the “upper left” corner of the trajectory, entering a building for 30 minutes, then starting the outdoor path again. As expected, accuracy inside the building was low, explaining the erratic measures recorded at that time. Table 2 shows the GPS time to first fix measurement, for each of the conditions. With both systems, arm TTFF was quicker than trunk TTFF, since that position gives a better clear view for the passive antenna. The IGotU performed better than the WIMU-GPS in that condition. However, when worn on the trunk, the WIMU-GPS is able to get a quicker fix than the IGotU. Globally, performance of the WIMU-GPS platform is adequate for activity monitoring, with a TTFF varying between 0:59 and 14:05, depending on the sensor position.

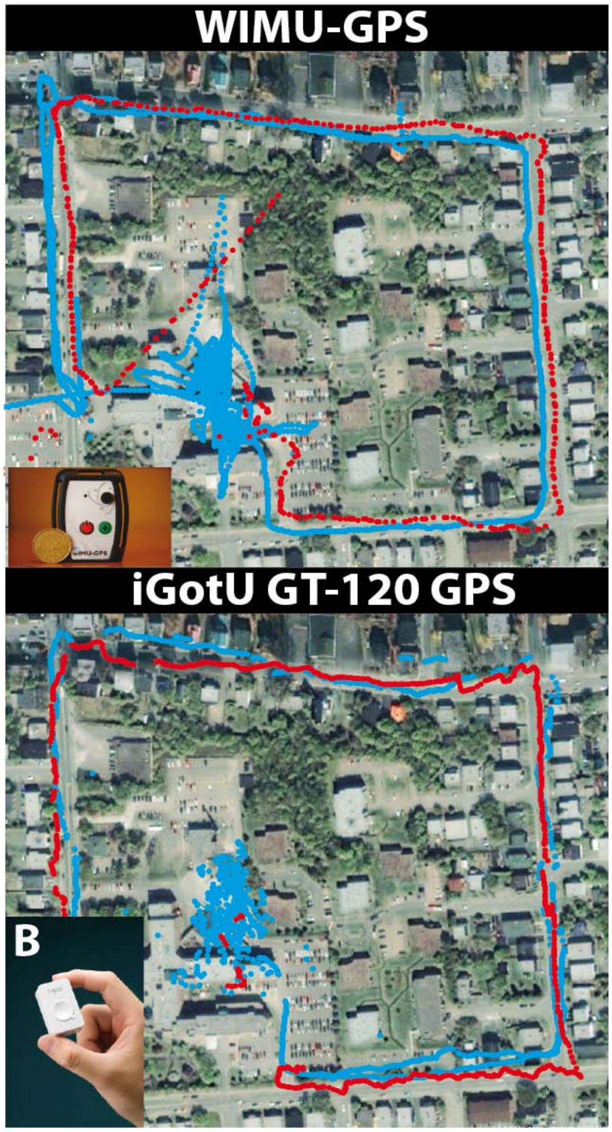


Figure 5. Trajectory comparison of the two GPS systems with the best (blue) TTFF and the worst (red).

TABLE 2. GPS TIME TO FIRST FIX UNDER COLD START SCENARIO (TTFF)

	WIMU-GPS		IGotU-120	
	Trunk	**Arm**	**Trunk**	**Arm**
Best TTFF (s)	86	59	61	43
Worst TTFF (s)	845	332	2942	149
Mean TTFF (s)	294	191	571	113
STD TTFF (s)	208	84	911	29

V. CONCLUSION

The combination of inertial sensing and GPS tracking in a light and compact wearable form factor with extended datalogging capabilities offers interesting possibilities to explore real life mobility of individuals with minimal interference in their daily activities. The WIMU-GPS platform initial specifications and performance show promising results for long term monitoring. The autonomy of the WIMU-GPS will however be a key factor in the generalization of this approach. While the autonomy can be enhanced with motion based power management and adjustment to the GPS chipset functions (duty cycle, sleep mode, trickle power mode, etc…), optimization will be needed as these implementations can also affect the accuracy and tracking performance of the GPS receiver under the condition of use tested (i.e. cold starts, in or out of buildings etc…). The study of lifespace and mobility can potentially provide unique insights into intrapersonal and environmental factors contributing to mobility restriction. External I/O allowing connection of various physiological sensors such as oxymeter, EMG and voice activity detection could enhances the range of potential applications of the platform. Further studies will however be needed to establish the validity and reliability of the WIMU-GPS in characterizing the lifespace and mobility profile of different patient populations.

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