Real-time Multi-Sensor Positioning for First Responders

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ABSTRACT

This paper describes a concept for real-time positioning of first responders that includes a number of complementary sensors worn by the first responder, to increase accuracy and robustness in indoor and complex environments. By using sensors of different types, each with their own strengths and limitations, and fusing their respective outputs, the goal is to increase the usability of positioning information in time-critical and risky operations. This facilitates synchronization of activities and increases safety in the operation. The sensors included in the proposed real-time positioning module are shoe-mounted inertial measurement units, ultra-wideband radio, thermal and visual cameras, and GNSS. The fusion framework is based on factor graphs. This work-in-progress paper describes the individual sensor components and shows preliminary findings concerning the possibilities to improve position estimation through sensor fusion.

Keywords

Positioning, real-time, multi-sensor, sensor fusion, first responders

INTRODUCTION

In time-critical, risky and complex missions, knowing the location of first responders (FRs) at any given point in time is important. It enables efficient coordination and assessment of mission progress, and supports informed and timely decision-making in rapidly developing scenarios. Accurate and up-to-date position-related information is also essential in emergencies when FRs need immediate assistance, e.g. to evacuate detected trapped victims, or in case a FR needs immediate assistance by fellow team members.

First responders face challenging operations in diverse and complex disaster sites that often involve combinations of outdoor and indoor environments. While receivers for global navigation satellite systems (GNSS) provide satisfactory accuracy in many purely outdoor scenarios, a technical challenge lies in creating complementary solutions that work well also in GNSS-denied environments, e.g. indoors, underground or in urban canyons. Many approaches for Indoor Positioning System (IPS) solutions have been suggested, spanning a vast range of sensor technologies that reflects the great diversity of exploitable phenomena for estimating position, as well as the large variety of imaginable conditions at the scene for which the IPS is intended. A positioning system should be able to seamlessly handle transitions between outdoor and indoor environments, be lightweight, small, inexpensive and power efficient, while providing the accuracy needed for the duration of the mission.

The availability of WiFi network coverage in many indoor environments have stimulated research on using such signals to estimate position (Liu et al., 2020). Such approaches are susceptible to multi-path effects and propagation loss caused by walls etc, but by recognizing stable features in the signal environment, so called

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fingerprinting, the accuracy can be increased. Errors below one meter were reported in (Kotaru et al., 2015) and machine learning approaches to further increase accuracy have been proposed (Khattak et al., 2022). Similarly, positioning using Bluetooth technology, especially Bluetooth Low Energy (BLE), is an active field of research as well (e.g. Paterna et al., 2017; Bai et al., 2020).

Additionally, advances in magnetic sensor technology have stimulated the development of positioning approaches exploiting static and subtle disturbances to the Earth's magnetic field created by the environment (Ouyang and Abed-Meraim, 2022). Although the positioning accuracy currently achievable with this technology is usually lower than that of other methods, it is interesting for future multi-sensor positioning systems as a means to increase robustness in especially challenging environments.

First response missions often involve time-critical activities in damaged infrastructure. Time does not allow setting up reference systems, the existence of functional local wireless networks cannot be assumed, and solutions cannot be based on the assumptions on pre-installed infrastructure in the building. As a consequence, FRs should be able to bring with them everything they need to position themselves, which implies that the equipment needs to be compact, portable and unobtrusive so as to not hinder or jeopardize the FRs ability to carry out their tasks. Rantakokko et al. (2016) proposed an approach to complement a GNSS receiver with shoe-mounted inertial navigation systems (INS) to provide a compact and easily wearable positioning system for combined outdoor-indoor environments, involving a cut-off criterion to discard unreliable GNSS readings. It was demonstrated that it can improve the position and heading accuracy in outdoor-indoor transition regions. The performance of shoe-mounted INS for positioning depends on the type and speed of movement of the wearer. In practice, as FRs often need to move quickly and unexpectedly, shoe-mounted systems need to be combined with other approaches to increase the robustness of the overall solution.

Positioning based on electro-optical sensing, in combination with visual-inertial odometry and SLAM (Simultaneous Localization and Mapping) methods, has been studied for many years and has reached a maturity level that makes it an important component in numerous robotics, automotive and entertainment applications. Börner et al. (2017) proposed a helmet-mounted IPS similar in concept to the one described in this paper although based on other estimation algorithms. Irmisch (2022) presents a recent survey of the field and highlights particular problems related to using visual positioning methods in dynamic and challenging first responder environments.

Every type of sensor technology has strengths and weaknesses and it is easy to anticipate situations where any single one would fail to perform satisfactorily. Therefore, the key to maintaining robustness and accuracy over time lies in combining several sensors into the same system. In fact, visual sensors are almost always accompanied by IMUs to support pose estimation in case of low contrast or imagery dropouts. For example, Mahmoud et al. (2022) incorporated a stereo camera module, IMUs, UWB ranging, and a laser scanner in a wearable system and performed accuracy assessments only to further underline the usability of each individual technology and the rationale to combine them in one system to improve overall accuracy and robustness.

For systems intended to be worn by first responders, or used in miniature sensor platforms, size, weight and power concerns become challenging, as sensors and sufficient data processing power need to be incorporated into lightweight, compact and energy-efficient packages. Research addresses the integration of visual and inertial information at raw data level to fully exploit the correlations between different sensor modalities on compact hardware (e.g. Delmerico and Scaramuzza, 2018; Sheikhpour and Atia, 2022).

In this paper, we propose an approach to positioning of first responders using cooperating person-worn sensors to increase robustness in different environments, the purpose being to allow test and validation of different configurations in realistic conditions.

THE REAL-TIME POSITIONING MODULE (RTPM) CONCEPT

The main objective is to position first responders in situations that they face during missions in complex environments. Fulfilling this objective implies addressing a number of challenges:

- **The environment is unknown beforehand.**
  It cannot be assumed that accurate maps exist when first responders commence a mission. Therefore, the positioning solution must be independent of reference maps.
- **The environment is GNSS-denied.**
  Buildings, underground structures and many other environments pose significant challenges relating to inaccuracy or total absence of GNSS signals.
- **No infrastructure for positioning installed.**
  During emergency situations it cannot be assumed that first responders have the time to set up reference positioning installations, which in practice translates into a requirement of positioning systems using

only sensors worn by the first responders themselves.

- **Each type of sensor has strengths and weaknesses.**
  No single sensor technology solves the positioning problem on its own, at least given practical side conditions concerning limitations in size, weight and costs. A technique may work well under a range of conditions but it is quite easy to set up a situation where a particular sensor would struggle. The key to improved positioning accuracy over time lies in combining several techniques.

The real-time positioning module (RTPM) for first responders addresses the above challenges. The RTPM is designed to explore the possibilities with complementary, cooperating sensor devices for positioning to give practitioners from different disciplines (search and rescue, firefighting, law enforcement, medical emergency service) the opportunity to learn and discuss how the functionality as such can be exploited and incorporated in future missions. The RTPM is also designed to be modular so that the user can choose to use only a sub-set of sensors depending on the conditions or requirements. In this paper, "RTPM Base" refers to a configuration of components intended as basic system that most first responders could use. Moreover, "RTPM Plus" denotes the Base system with the addition of a camera-based positioning system intended for helmet-mounting.

The RTPM Base consists of the following components (see Figure 1):

- Shoe-mounted positioning devices
- Ultra-wideband (UWB) radio units
- GNSS receiver and antenna
- Raspberry Pi 4 computer for sensor fusion and communication

The RTPM Plus combines the above components with a helmet-mounted camera SLAM system including both a

- Near-infrared stereo camera system
- Thermal stereo camera system
- Additional IMU co-located with the cameras

Both camera systems are encapsulated in one module for helmet-mounting offering ease of testing and validation with first responders (Figure 2**.**). The RTPM Plus also contains an NVIDIA Jetson NX embedded computer, on which the SLAM algorithm runs. Specifically, the graphics processing unit is used to find points of interest, so called landmarks, in images from the cameras.

Figure 1. The components of the RTPM Base system for first responders. Left to right: IMU modules for shoe-mounting, a Raspberry Pi 4 computer, a UWB radio module, and a GNSS receiver and antenna.

Figure 2. The combined thermal and near-infrared stereo camera SLAM systems in a helmet-mounted module of RTPM Plus.

SHOE-MOUNTED POSITIONING DEVICE

The shoe-mounted positioning sub-system of the RTPM is based on the inertial navigation concept further described in Rantakokko et al. (2016). The current version of the device has been updated in terms of connectivity and is easily strapped onto any kind of shoe for experimentation purpose (Figure 3), while in the future, this kind of sensor components could be integrated into the FR's boots. The device is based on an IMU sensor measuring accelerations and rotations, and a signal processing unit that filters and integrates the data into a position estimate.

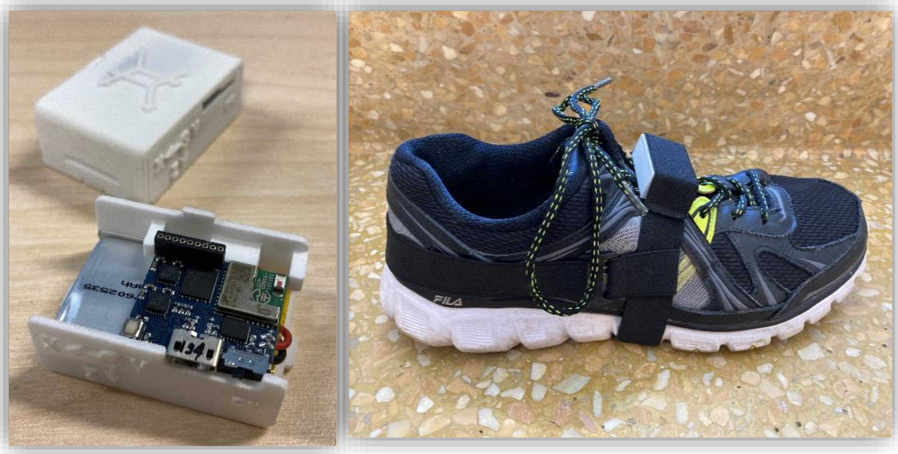

Figure 3. Left: The MIMU22BLXP IMU module. The device integrates the IMU data between ZUPTs and sends each step by Bluetooth to the user. Right: IMU module strapped to a shoe.

The device is based on the ZUPT (Zero velocity UPdaTe) principle, illustrated in Figure 4. The three-axis gyro sensors provide a means to estimate the attitude of the IMU, used for transforming the accelerometer measurements to an earth-bound coordinate system. This allows for subtracting the effects of gravity from the accelerometer measurements, whereby a velocity estimate is obtained after integrating the accelerometer measurements, and the position estimate is obtained after a second integration. Whenever zero velocity is detected, that information can be used as a ZUPT to correct the orientation in roll and pitch and thus to compensate for integrated errors in the subtraction of gravity as well as a reset of the velocity to zero until a new step is taken. This principle is exploitable as the sensors are mounted on the boots of someone walking or running. During a walking or running cycle, the measured velocity of each foot approaches zero at some point when the boot is in contact with the ground. By recognizing instances of zero velocity, the drift can be minimized.

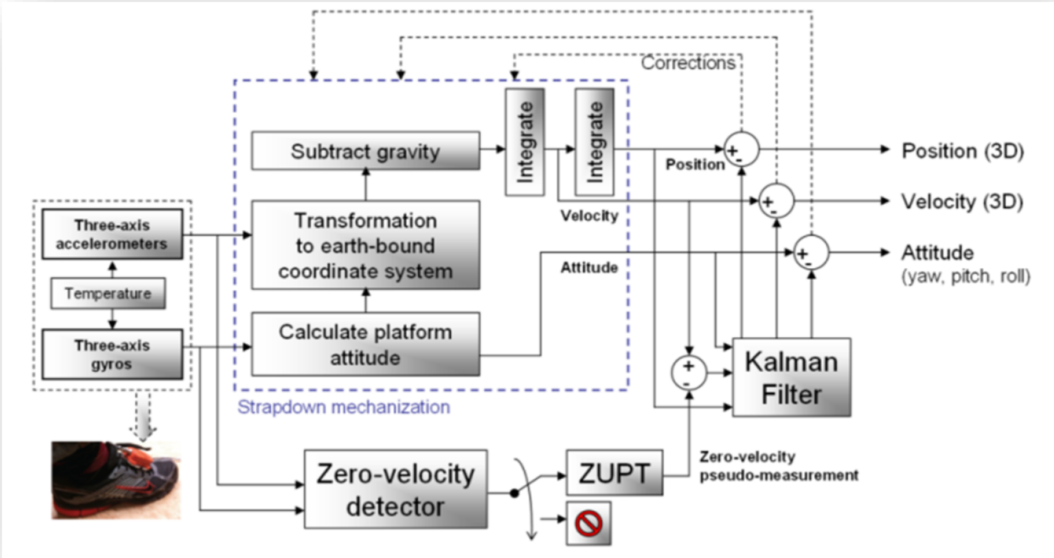

Figure 4. Illustration of the principle of shoe-mounted RTPM device.

The IMUs are MIMU22BLPX manufactured by Inertial Elements. The devices communicate via Bluetooth Low Energy (BLE) with a Raspberry Pi 4 computer that communicates the position estimates to where the information is requested, be it other nearby units, the team leader or on higher command levels. They are configured as Pedestrian Dead Reckoning (PDR) sensors, which means that all dead reckoning computations are done in the module. For each step detected by the module it outputs the displacement in *x*, *y* and *z* axes, as well as the change in heading from previous steps, along with an estimation of the displacement uncertainty. The device has a battery that lasts for up to eight hours of operation.

ULTRA-WIDEBAND RADIO UNITS

The RTPM system also consists of ultra-wideband radio (UWB) devices for positioning of group members relative to each other. The UWB units measure distances between the individual RTPM devices. The purpose of the UWB sub-system is to “glue” individual RTPM devices together by detecting and correcting for positioning errors that would otherwise eventually make stand-alone separate RTPM devices diverge in the absence of GNSS signals. The technique *per se* is rather straightforward; the devices measure the range to each other and then estimate position through triangulation. The UWB radio module DWM1001 (Figure 1, top) from Qorvo (formerly Decawave) is used to measure the distance between RTPM systems. The distance measurements will degrade if the other units are not within line of sight.

THERMAL STEREO CAMERA SYSTEM

A thermal stereo camera sub-system of RTPM is intended to be mounted on a FR’s helmet. It consists of two thermal cameras, one IMU unit and an NVIDIA Jetson NX computer that runs a Simultaneous Localization and Mapping (SLAM) algorithm. The thermal camera model used in the prototype system is the short-lens version of the FLIR Boson – a longwave infrared (LWIR) thermal camera with a resolution of 640 x 512, HFoV 95°. The camera weight is 21 grams, including the optics. Each camera also has an external interface module of 2.6 grams for synchronization between the cameras and with the inertial measurement unit. The system utilizes two thermal cameras (of the same type) to achieve stereo vision, which is beneficial for SLAM systems, since the distance to observed objects can be estimated from a single pair of images. The navigation is based on landmark tracking, following points of interest while the system moves through the environment.

The IMU co-located with the cameras measures acceleration and angular velocity and provides samples at 100 Hz, while the cameras operate at a lower frequency of approximately 10 Hz. This relatively low frame rate is chosen to limit the computational requirements of the system. Data from the IMU is used to predict where previously tracked landmarks are expected to appear in a new image. This simplifies the association between tracked and observed landmarks. When the system moves through an environment with no landmarks, the SLAM algorithm relies on the IMU, making it possible to maintain a good pose estimate for a few seconds. After too long periods without landmarks to track, the SLAM system no longer provides accurate positioning. This is one example of a case where fusion with other positioning systems is needed.

Figure 5 illustrates an early experiment carried out to assess feasibility of the approach and test algorithms before implementation on target hardware. The conclusion from the test was that thermal-based SLAM works well, provided there is enough heat contrast in the images. In this particular example, the scene contained a train in operation, the interior of which was considerably hotter than the environment providing the SLAM system with many stable landmarks. In this experiment, cameras with lower resolution and a smaller field of view (320 x 256 pixels and approximately 50 degrees horizontally) were used. This obviously decreases the achievable positioning accuracy compared to the cameras used in RTPM Plus.

This approach to positioning and mapping with stereo thermal cameras system was suggested in Emilsson and Rydell (2014). The concept has been developed to address needs of FR and military personnel concerning increasing safety and efficiency of operations in smoke-filled and dark environments.

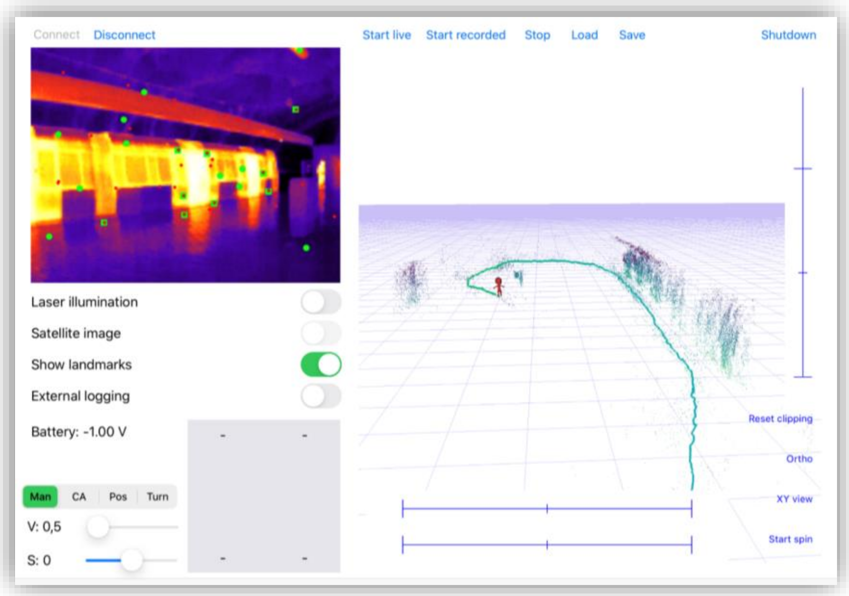

Figure 5. Screenshot from an early feasibility test using a thermal camera-based SLAM test rig (cameras mounted in a hand-carried box rather than mounted on the helmet).

VISUAL STEREO CAMERA SYSTEM

The RTPM Plus also contains a RealSense D435i, a stereo camera with built-in IMU. The camera is sensitive to near-infrared and visible light and has a resolution of 848 x 480 pixels, with a horizontal field of view of approximately 90 degrees. A SLAM algorithm, very similar to that described for the thermal cameras above, is used to estimate the user’s position based on tracking landmarks in images from the cameras. Also similar to the thermal case, the IMU is used to predict landmark positions and to provide positioning when no landmarks are available. The algorithms for simultaneous localization and mapping are described in detail in Rydell and Emilsson (2013) and Rydell et al. (2016).

In early experiments, the Realsense-based SLAM system and the thermal SLAM system were developed and tested separately. In the RTPM Plus system, the different cameras will instead provide data to the same instance of a SLAM algorithm. This is expected to significantly increase the robustness, since the combined system can maintain accurate positioning as long as landmarks are visible to either the visual or thermal camera pair. Combining several sensor types in one navigation algorithm is one form of sensor fusion. This, however, is unlike the fusion presented in the next section, where individual positioning results from separate systems are fused with each other.

SENSOR FUSION FOR INCREASED ROBUSTNESS

The purpose of fusing sensor outputs is to maintain better accuracy during longer periods of time and in varying conditions. The ultimate goal is to feed all position-related data from all sub-systems into one fusion framework. To be tractable, we divide the problem into smaller portions where fusion of a sub-set of sources is studied.

FUSION OF SHOE-MOUNTED DEVICES AND UWB RANGE MEASUREMENTS.

The data from the shoe-mounted sensors are processed using the GTSAM framework (Dellaert, 2012). A major advantage of GTSAM is that it allows for optimization of the whole trajectory (for reasonably long periods). Figure **6** shows an early example of GTSAM based fusion data from the shoe-mounted devices and UWB range measurements. The range measurements of the UWB keep the position estimates in check and prevents them from diverging, which could otherwise happen in the absence of the UWB component and then there would be no way for the shoe-mounted sensors to recover. Figure **7** illustrates the value of adding UWB range estimates to the RTPM concept to increase accuracy over time.

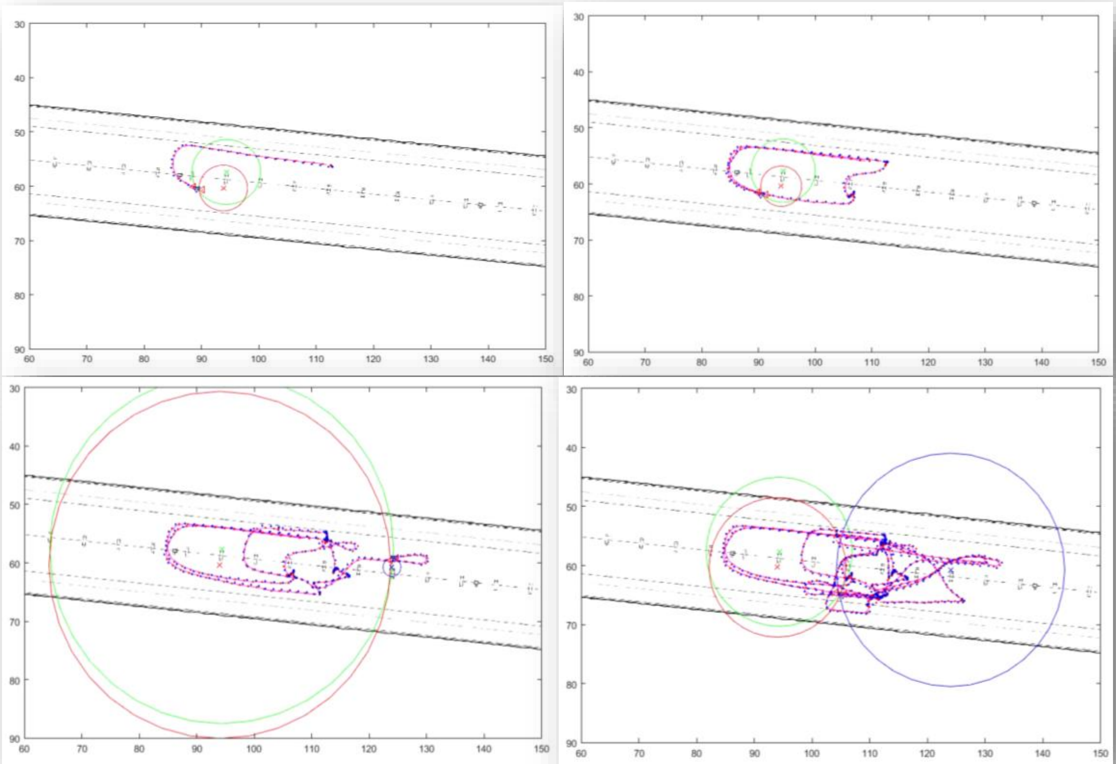

Figure 6. An example with an approximately three minutes long sequence of combined UWB and shoe-mounted IMU measurements. In this early experiment, only one UWB device was moving and the other three were stationary, acting as beacons. The circles indicate the estimated range from each of the three UWB beacons to the moving UWB devices, and the red and blue trajectories show the resulting estimates of position of the left and right shoe-mounted devices, respectively.

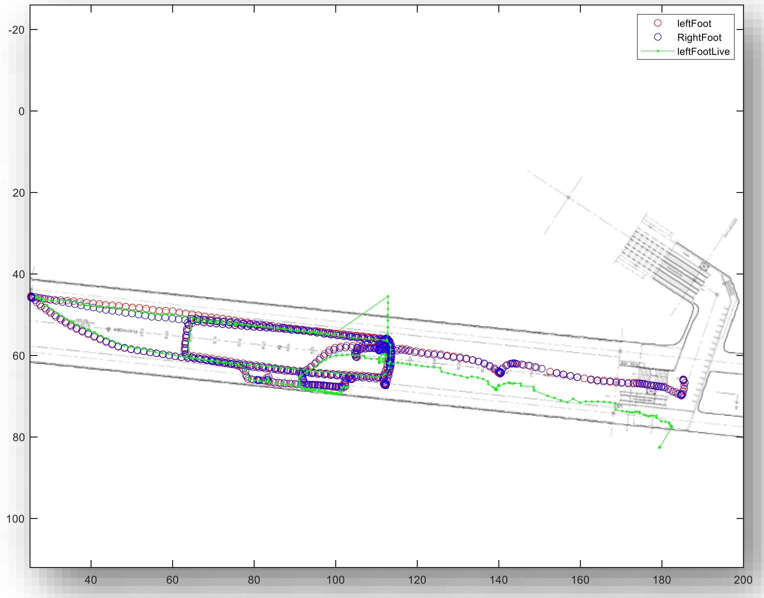

Figure 7. Example of fusion of UWB and shoe-mounted devices during a couple of minutes long walk on a train platform. The green trajectory shows the drift in an uncorrected shoe-mounted device, the position estimate of which ends up being approximately ten meters off at the end of the walk. Blue and red circles show the estimates for the right and the left foot, respectively, aided by UWB range estimates. The results indicate that using UWB range measurements can help maintain positioning accuracy over time.

In the examples above, the computations were done off-line. Current development addresses validation of a real-time implementation of the algorithm that allows for simultaneous estimation of many devices at once. The on-line implementation utilizes the Robot Operating System (ROS) for transport and synchronization of the sensor data, and a GTSAM based fusion algorithm utilizing iSAM2 developed by Kaess et al. (2011).

The algorithm estimates the pose of each foot incrementally by utilizing incoming velocity readings and binding consecutive poses together. The estimated poses of the left and right foot, respectively, are then bound together by estimating the stomach pose mid-way through the current processed step. The pose of the stomach mid-step is estimated as half the foot sensor reading of the current processed step, which ideally should coincide with the other foot in the axis of direction. The mid-step pose is then bound together with the other foot using a range constraint based on the distance between the navel and foot of an average person. Figure 8 illustrates the feet pose estimation process.

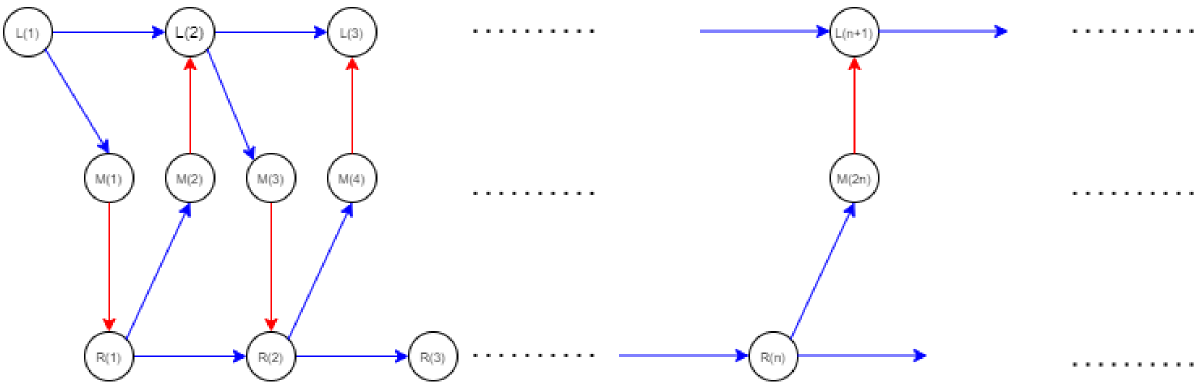

Figure 8. Illustration of the feet pose estimation. Circles indicate foot poses, and the arrows indicate factors relating these. The blue factors are GTSAM between factors based on the velocity readings from the foot sensors. Red factors are GTSAM range factors, given by the constraint of distance between stomach and foot of a person of height 1.8m.

Preliminary tests have been conducted to verify the flow and synchronization of data fed to the algorithm. Figure **9** shows an example of online positioning from such a test, utilizing the foot mounted sensors and four stationary UWB anchors.

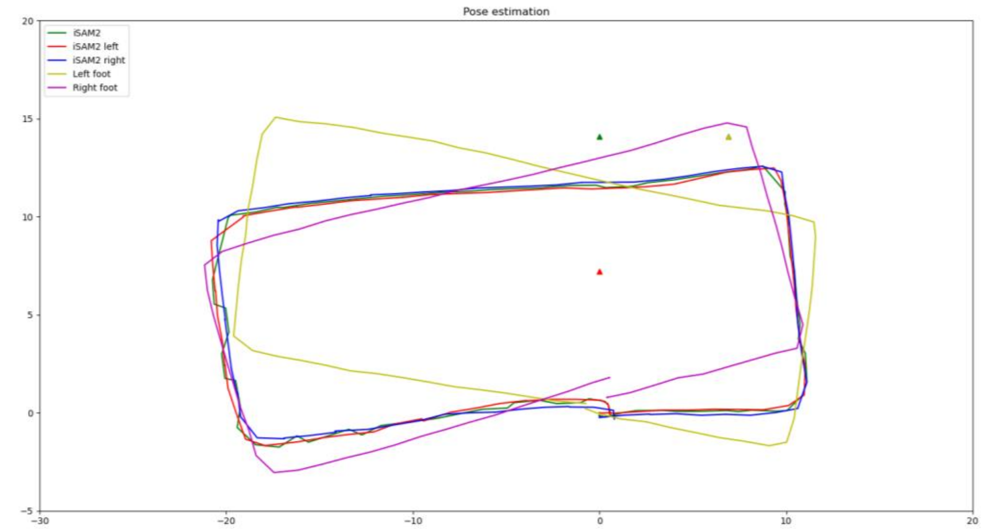

Figure 9. An example position trajectory computed on-line. The estimated positions of the respective feet produced by double integration can be seen in yellow and magenta. The red, blue, and green trajectories show the estimated positions produced by the fusion algorithm.

FUSION OF GNSS AND CAMERA SLAM.

The RTPM should be able to utilize GNSS signals when available, to use as reference for a starting point before entering a GNSS-denied environment, and to correct for errors when reacquiring GNSS signals. The main challenge is to use the GNSS in combination with other RTPM sub-systems in such a way that transitions from outdoor and indoor environments become seamless. In particular, we want the RTPM to be able to correct its recent trajectory and snap onto a reliable GNSS reading so that the resulting trajectory is smooth.

GTSAM-based fusion of camera SLAM and GNSS has been implemented as an iOS app, which runs in real-time on an iPhone 12 Pro or later. In this case, the camera SLAM algorithm is part of Apple's ARKit, which uses an IMU and one or more of the cameras available on the phone to estimate the position and orientation of the device. The trajectory estimated by ARKit is split into one-second intervals, and a GTSAM factor graph is built such that the relative motion within each interval constitutes a factor between poses. When GNSS is considered reliable, the GNSS position estimate is used as an additional factor for the latest pose (see Figure 10).

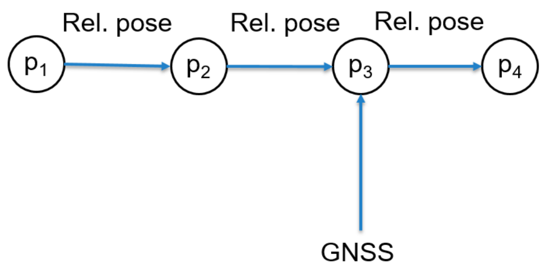

Figure 10. GTSAM factor graph with poses, factors representing relative motion between them, and a factor representing a position measurement from GNSS.

Similar to the fusion between foot-mounted IMU and UWB, presented above, the entire trajectory is recomputed when new measurements become available. This essentially means that even if the camera SLAM system drifts from the correct position when GNSS is unavailable, any accumulated errors can be corrected when reliable GNSS measurements arrive, for example when exiting a building. This is illustrated in Figure 11, which shows estimated trajectories overlaid on a map. The left part of the figure illustrates the trajectory a few seconds *before* exiting the building, while the right part shows the corrected trajectory a few seconds *after* exiting. Once outside the building, acquired reliable GNSS measurements are fed into the factor graph, upon which the indoor segment of the trajectory is automatically adjusted to produce the best overall estimation of the entire trajectory.

Figure 11. Estimated trajectories *before* (left) and *after* (right) exiting a building.

The most difficult part of this algorithm is knowing when GNSS measurements should be considered reliable. In the current implementation, this is based on the uncertainty reported by the GNSS module in the phone. These uncertainties are sometimes significantly underestimated, which can cause positioning problems. Hence, ongoing work aims at improving the reliability estimation, for instance by comparing short trajectory segments from the camera-based system and from GNSS.

CONCLUSIONS AND FUTURE WORK

Knowing the position of team members facilitates sharing of time-critical information, e.g. to quickly pinpoint the location of detected victims or features of interest, to monitor mission progress and to coordinate activities for increased search and rescue or law enforcement operation efficiency. This paper describes the current state of research towards a person-worn, multi-sensor system intended to position first responders reliably in challenging environments.

Each of the sensors included in the proposed real-time positioning module (RTPM) concept has strengths and weaknesses. Shoe-mounted IMU sensors are accurate during normal movement (walking), but susceptible to errors during fast and unexpected types of movements and since they have no perception of the world or connection to any reference system they cannot recover from errors on their own. UWB radio measurements are efficient to keep errors of individual RTPM devices at bay but experience difficulties in cluttered environments, e.g. containing many walls that degrade signal quality through reflection and attenuation effects. Camera-based SLAM techniques including stereo thermal cameras are accurate as long as there is enough contrast and texture to allow for stable recognition of landmarks across images, but struggle in environments offering low contrast or too repetitive patterns. Fusing several types of sensors increases the likelihood of robust estimation across different types of environments and during different types of movements of first responders. The main conclusion is that fusion indeed helps reducing errors over time but that technical issues related to system initialization, data synchronization, stability and tuning of fusion parameters need to be addressed before it reaches its full potential.

Being work in progress, experiments shown in this paper are intended only as indicatory of the basic concept. Gathering empirical data to quantify performance is a natural and needed next step after the completion of all components. Future work will focus on fusion of the sub-systems in the RTPM, including evaluating the performance of different system configurations under different conditions (environments, movement patterns, etc.) and tuning parameters related to GNSS cut-off criteria to enable seamless outdoor/indoor transitions.

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