Journal of the Indian Institute of Science
A Multidisciplinary Reviews Journal
ISSN: 0970-4140 Coden-JIISAD

REVIEWS

A Prototype of a First-Responder Indoor Localization System

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Abstract | In this paper we present an approach to build a prototype model of a first-responder localization system intended for disaster relief operations. This system is useful to monitor and track the positions of the first-responders in an indoor environment, where GPS is not available. Each member of the first responder team is equipped with two zero-velocity-update-aided inertial navigation systems, one on each foot, a camera mounted on a helmet, and a processing platform strapped around the waist of the first responder, which fuses the data from the different sensors. The fusion algorithm runs real-time on the processing platform. The video is also processed using the DSP core of the computing machine. The processed data consisting of position, velocity, heading information along with video streams is transmitted to the command and control system via a local infrastructure WiFi network. A centralized cooperative localization algorithm, utilizing the information from Ultra Wideband based inter-agent ranging devices combined with the position estimates and uncertainties of each first responder, has also been implemented.

Keywords: *Personal Navigation System, Inertial Measurement Unit, Kalman Filter, Indoor Navigation, Cooperative Localization.*

1 Introduction

There has been an increasing demand for a robust and accurate positioning system that works in indoor and outdoor environments. GPS provides a whole range of navigation accuracies at very low cost and low power consumption. The devices that use GPS are portable and are well suited for integration with other sensors, communication links, and databases. The need for alternative positioning system arises because GPS does not work in all environments, especially indoor environments. This is a major problem in certain situations, such as military and disaster relief operations, where one has to track the first responders who arrive at the scene to carry out their mission. Over the past several years, the need for tracking systems in indoor environments has seen a sharp rise. In India, over 100,000 deaths occur annually due to fires in homes and workplaces and an estimated 6,000 fires occur in homes in Sweden. In Sweden, the preliminary figures for 2012 indicate that about 110 people died in fire accidents, and a vast majority, about 90 people, died in residential fires. The number of fatalities has not changed significantly over the past 20 years despite smoke alarms, fire extinguishers and large efforts regarding information campaigns.

The methodology used in fire-fighting operations varies between countries. Using Sweden as an example, a fire-fighting team responding to an alarm typically consists of two smoke-divers, one smoke-diving supervisor, one fire-fighter responsible for supplying water and a sector chief (who assumes the role of an Incident Commander, if only one team is assigned to the task). At larger apartment fires, or those occurring in public buildings (e.g. restaurants, shops or schools), two or more of these five-man teams are called in from

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different fire stations. Smoke diving operations are performed with fire-fighters working in pairs with short distances between them and whilst always carrying the water hose. These operations are performed in situations whenever lives are in danger. The water hose is the most important safety feature; it is used as a self-protection measure against nearby fires and it also serves as the evacuation route guide for the fire-fighters if they need to extract rapidly. A smoke-diving supervisor will position himself just outside the danger area, with the main tasks of keeping track, via radio, of the positions and activities of the smoke-diving team, judging the current threat level (including the risk of fire gas explosions) and deciding upon the tasks to be executed by the smoke-diving team. The smoke-diving supervisor is equipped with breathing apparatus and carries his own water hose, enabling him to aid or rescue the smoke-divers if needed. One supervisor can be responsible for multiple smoke-diving teams operating within the same area, and additional smoke-diving teams can be assigned to protect the escape routes of the first team and be ready to assist them when needed.

Fire-fighters that enter buildings, which are on fire, experience very difficult conditions. The heat generated by the fire in combination with the weight of the personal protection equipment and water hose may cause exhaustion. Combined with high stress levels in smoke-filled or dark environments (which can be expected during power outages caused by the fire) there is an apparent risk for disorientation. Hence, there is a significant risk that the smoke-divers, due to disorientation experienced during strenuous operations, are unable to correctly describe their movements to their supervisor, or that the smoke-diving pair gets separated from each other and the water hose. An accurate positioning system could enable an alarm functionality which could prevent these life-threatening situations where fire-fighters get lost.

Depending on the role, fire-fighters have different information requirements and the main identified user needs (system functionalities) are presented in Table 1. For the smoke-divers, any localization system will primarily increase their safety; however, for the sector chief, the technology provides a means to rapidly comprehend what the situation is like and how to deploy resources, especially in large incidents with multiple fire stations deployed at the scene. Automatic mapping capability is an important complement to the localization technology, since fire-fighters are not expected to have access to building floor-plans.[1] While law enforcement officers, fire-fighters, and military personnel have varying requirements for localization and tracking systems, all three groups share certain key requirements, as summarized in Table 2.

In addition, other applications like location of elderly in care-centers, localization of customers in a shopping mall for targeted advertising and of employees in an organization are some scenarios where indoor positioning is required and has seen increasing demand.

1.1 *Existing technologies*

There are several technologies which are being used for indoor positioning. Some of them are based on WiFi or Ultra-WideBand (UWB).[2] These technologies assume an infrastructure like a WiFi network or a UWB network being available in the area of interest. The accuracies provided by these technologies range from a few cms to a few metres.[2] However, in the case of harsh environments like a disaster-affected building, such assumptions of infrastructure cannot be made. Therefore, there is a need for developing autonomous positioning systems.

The main challenge in developing an infrastructure-free positioning solution is to create a technology that is sufficiently accurate in GPS

Table 1: Information requirements and user needs for fire-fighters.

Role and task	Identified user need and action
Smoke-diving: Search area for persons and suppress fire.	Alarm when separation between smoke-divers and/or when distance to water hose too large. Provide navigation guidance to colleague.
Supervisor: Keep track of smoke-divers and fire gases and other risks, assist if needed.	Situation Awareness. To know the positions of all team members and provide directions to find fire-fighters in distress.
Sector chief: Strategic decisions on how to perform mission (within specified sector). Enable rapid and efficient replacements of personnel (primarily indoors). Coordination, between sectors and with incident commander.	Situation Awareness. Positions of fire-fighters, indoors and outdoors, and other available information on dangerous goods, escape routes, fire information, maps etc. to provide a means for those in-charge, to understand the situation.

Table 2: First responder key requirements.

1.	Horizontal plane location accuracy: <1 [m].
2.	Vertical plane location accuracy: <2 [m].
3.	Constant accessibility for those who need the positioning data.
4.	Physical robustness for operation under harsh conditions.
5.	Encrypted voice communications and data transfer.
6.	Integrity monitoring, with automatic estimation of localization errors (uncertainty) combined with detection and warning in case of electronic attack.
7.	Data format compatible to and integrated with other information, in particular personal health status.
8.	Real-time map-building capability.
9.	Lean design for integration into individual's uniform.
10.	Weight: <1 [kg].
11.	Battery power: >24 [hours].
12.	Visualization: intuitive and easy to understand.
13.	A modular system.
14.	No pre-installation.
15.	In any armed operation, the visualization system should present heading to own units and in particular the heading of the weapon. Data for distance and direction to targets and threats should also be presented.
16.	Cost: <1000 [EUR].

denied environments. Since Inertial Navigation System (INS) technology is capable of working in almost all environments where GPS has difficulties, Microelectromechanical systems (MEMS) inertial technology is seen as both a possible complement of GPS technology and a potential alternative to GPS. For example, INSs can provide position information whenever GPS signals are unavailable (in tunnels, indoors, underground facilities), ensuring a possible seamless provision of position information. However, a foot-mounted INS, with low-quality inertial sensors, will not work if it is not fused with other information when the subject is on a moving platform such as a train or vehicle. Fortunately, both systems can provide information, which can be fused in an optimal manner to obtain good accuracies in the position estimates.

This chapter presents a brief overview of the collaborative work carried out at the Indian Institute of Science, Bangalore and KTH Royal Institute of Technology, Stockholm, as part of the Indo-Swedish activity, which is jointly funded by the Department of Science and Technology, Government of India and VINNOVA, Sweden.

2 Foot-Mounted Inertial Navigation System

In Fig. 1, a block diagram of a strap-down INS is shown. The INS comprises the following two distinct parts, the Inertial Measurement Unit (IMU) and the computational unit. The former provides information on the accelerations and angular velocities of the navigation platform relative to the inertial coordinate frame of reference. The angular rotation rates observed by the gyroscopes are used to track the relation between navigation platform co-ordinate system and the navigation coordinate frame. This information is then used to transform the specific force observed in navigation platform coordinates into the navigation frame, where the gravity force is subtracted from the observed specific force. The accelerations in the navigation coordinates are integrated twice, with respect to time, to obtain the position of the navigation platform.

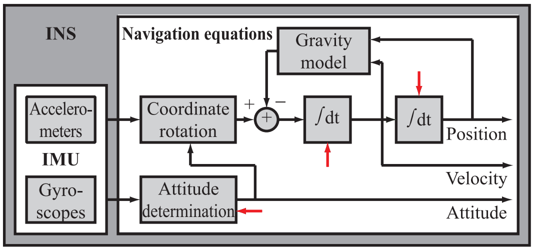


Figure 1: Conceptional sketch of a strap-down INS. The red arrows indicate possible points for insertion of calibration (aiding) data.

The navigation calculations in INS involve integration with time, which provide a low-pass filter characteristic that suppresses high-frequency sensor errors but amplifies low-frequency sensor errors and initialization errors. This results in a position error that grows without bound as a function of the operation time and where the error growth depends on the error characteristics of the sensors and the initialization error. In general, it holds that for a low-cost INS, a bias in the accelerometer measurements causes position error growth that is proportional to the square of the operation time, and a bias in the gyroscopes causes position error growth that is proportional to the cube of the operation time (due to an extra integration to obtain the relative angle between the navigation frame and body frame). The detrimental effect of gyroscope errors on the navigation solution is due to the direct reflections of the errors on the estimated attitude. The attitude is used to calculate the current gravity force in navigation coordinates and cancel its effect on the accelerometer measurements. The errors in the cancellation of the gravity acceleration are then accumulated in the velocity and position calculations. For a low-cost INS using gyroscopes with a bias on the order of 0.01 [°/s] this means that the position error is more than 10 [m] already after 10 [s] of operation.

Clearly, a navigation system which has such an error growth, is basically useless for indoor navigation. However, by utilizing the fact that an INS mounted on the foot of the user regularly becomes stationary, i.e., has zero instantaneous velocity, the errors in the INS can be estimated and partly compensated for, and the devastating cubical error growth can be mitigated.

In Fig. 2 a block diagram of zero-velocity aided INS is shown. The zero-velocity aided INS comprises the following three distinct parts, the INS, the zero-velocity detector and the Kalman filter; the Kalman filter has a state-space model describing how the errors in INS develop with time.[3] The INS works as the backbone of the system, continuously estimating the navigation state of the system. Whenever the zero-velocity detector detects that the system is stationary (close to zero instantaneous velocity), this information is used as an input to the Kalman filter that estimates the errors in the estimated navigation state. The estimated errors are used to correct (calibrate) the internal states of the INS.

The detection of the zero-velocity events can be done using external force sensors or radar sensors,[4,5] sensing when the shoe is in contact with the ground. However, external force sensors are prone to mechanical fatigue and may fail to detect that the foot is stationary in situations such as when the user sits down and does not apply his weight on the shoe. Radar sensors require costly electronics and they can not detect zero-velocity events if the radar (sole) is not directed towards the ground, e.g. when the user is crawling. Therefore, the zero-velocity events are generally detected directly from the IMU data, assuming that when the foot-mounted INS is stationary, the angular rate of the system is zero and the specific force vector is constant with a magnitude equal to the gravity force. In Ref. 6, the generalized likelihood ratio test (GLRT) detector for the zero-velocity detection problem is derived, and it is shown that in

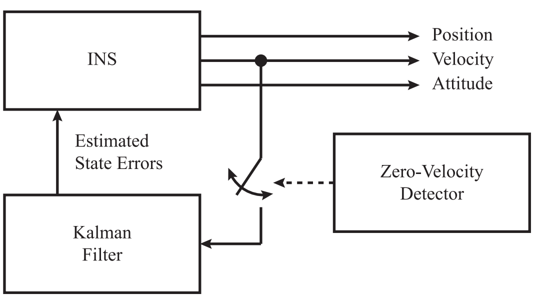
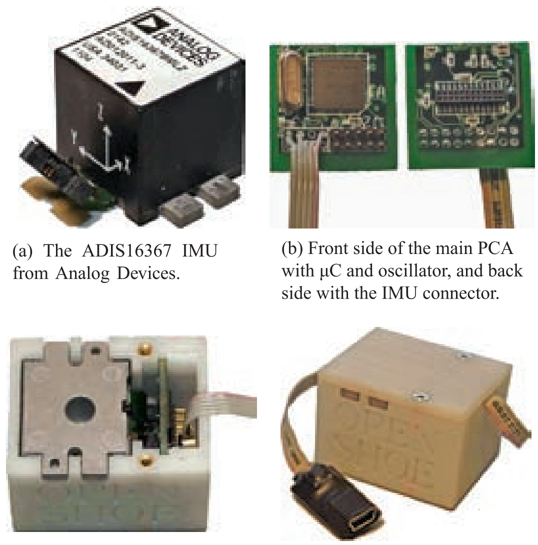


Figure 2: Conceptional sketch of a zero-velocity aided INS. The zero-velocity detector controls the data flow from the IMU to the Kalman filter. The Kalman filter estimates the errors in the INS and corrects (calibrates) the internal states of the INS.

Figure 3: Shoes with the OpenShoe foot-mounted INS implementation integrated in the heels.



(a) The ADIS16367 IMU from Analog Devices.

(b) Front side of the main PCA with μC and oscillator, and back side with the IMU connector.

(c) The system casing body with grooves to hold the IMU and the main PCA in place.

(d) The system assembly without the casing lid.

Figure 4: Main hardware components and assemblies of the OpenShoe foot-mounted INS implementation. The dimensions of the full assembly are 28.5 × 32 × 40.5 [mm].

literature, the most commonly used zero-velocity detectors are special cases of the GLRT detector. In Ref. 4 the performance of different zero-velocity detectors is evaluated.

The foot-mounted INS can clearly be used for pedestrian localization. However, for this purpose, an actual implementation is required. This gives rise to a number of practical issues. The OpenShoe project activity has designed and developed a foot-mounted inertial navigation system module, which can be embedded into the sole of a shoe.[7] Refer to Fig. 3 and Fig. 4 for details. The OpenShoe module is fully open source and the design documents can be found at www.openshoe.org.

3 Dual Foot-Mounted Inertial Navigation System

Although the errors in the INS can be estimated using zero-velocity updates, the position and heading error of the INS remains unobservable, and grows (slowly) without bound. Therefore, to reduce the error growth rate further, and to make the indoor localization system more robust, the users are equipped with two foot-mounted INS (one on each foot) and the navigation solution of the two systems are fused.

Since the human body is non-rigid, the relative positions of the foot-mounted INSs are not fixed, and one cannot directly relate the navigation solution of one foot-mounted INS to another. However, as illustrated in Fig. 5, there is an upper limit on how far apart the two foot-mounted INS can be, and the fusion of the two navigation solutions can be viewed as a filtering problem with non-linear inequality constraints. Several non-linear inequality constraint filtering methods have been derived and used to fuse the navigation solution from two foot-mounted INSs. See Table 3 for a list of non-linear inequality constraint filtering methods that have been tested and references to the papers describing the details behind them.

To illustrate the benefits of using two foot-mounted INSs, a user equipped with one OpenShoe navigation system on each foot walked 110 meters on level ground along a straight line at a normal gait speed (approx. 5 [km/h]). Twenty such trajectories with 4 different OpenShoe units (different IMUs) were recorded. To get the same initial and final positions and a heading reference, plates with imprints of the shoes were positioned at 0 [m], 10 [m], and 110 [m]. The initial heading was set such that the estimated position at the 10 [m] plate, without using the constraint, was on the x-axis. The inertial measurement unit data collected from

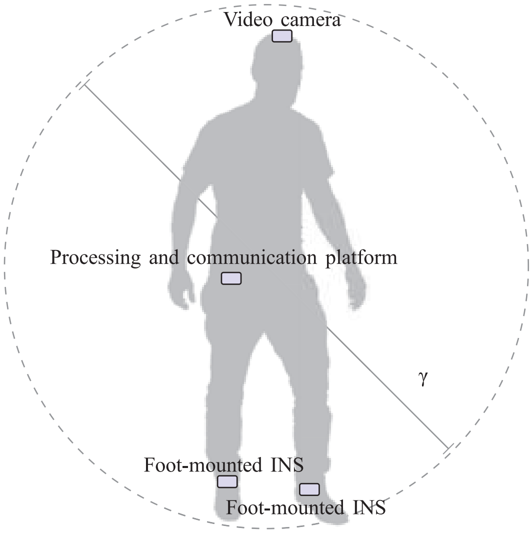


Figure 5: Illustration of the placements of the subsystem in a pedestrian navigation system and the maximum spatial separation γ between the foot-mounted inertial navigation systems.

Table 3: Different algorithms (methods) that can be used to fuse the information from two foot-mounted inertial navigation systems.

Algorithm	Method	Ref.
Sphere limit method	Constrains the stride length between two shoes when one shoe is stationary.	[8]
Centroid method	Constrains the stride length between two shoes at all time instants.	[9]
Constrained least squares method	Projection of the joint state estimate, using a constraint least squares algorithm, onto the subspace where the constraint is full filled.	[10]
Bayesian method	A Bayesian inference based approach, using a sigma point transformation.	[11]

the two navigation systems was then processed with the nonlinear inequality constraint filtering approach described in Ref. 10. The processing was done with the maximum foot-to-foot distance set to infinity, giving two uncoupled systems, and set to 1 meter, giving the constrained system. The estimated trajectories for three different fusion algorithms are shown in Fig. 6. Corresponding scatter plots with the 1-σ confidence ellipses of the final horizontal

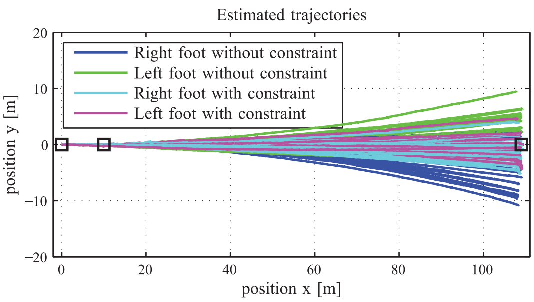


Figure 6: Estimated trajectories from walking along a 110 [m] straight line. The black boxes indicate the location of the starting position (0 [m]), the heading reference point (10 [m]), and the stop position (110 [m]).

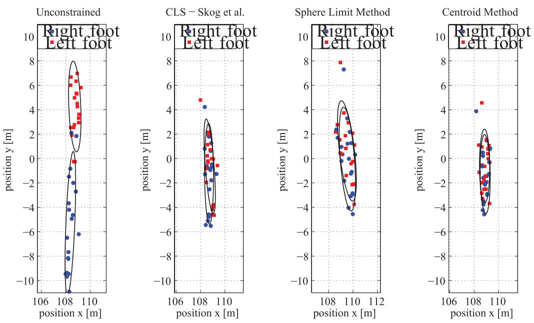


Figure 7: Scatter plot of end position of the two systems with and without the range constraint. $1-\sigma$ confidence ellipses are shown in black. The estimates from right foot and left foot are shown in red and blue respectively. It is clearly seen that the mean error and covariance of the final position estimates are significantly reduced by applying the range constraint.

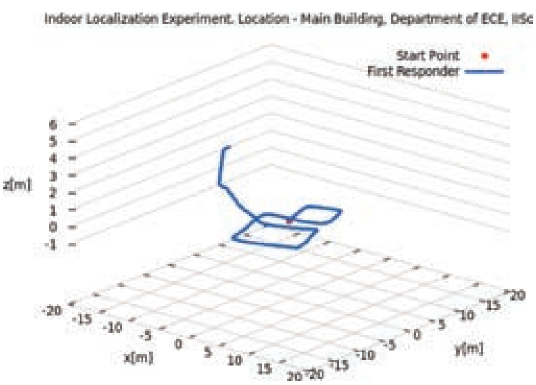


Figure 8: Sample 3-D trajectory of a person walking on a floor and climbing the stairs.

position estimates are shown in Fig. 7. Applying the constraint can be seen to have significantly reduced the mean error and covariance of the final position estimates.

Figure 8 shows a sample trajectory, obtained by one person walking in the Main Building, Department of ECE, IISc. Note that the person started on the ground floor and walked in a loop on the same floor and then proceeded to climb the stairs to reach the next floor. The change in x,y,z position is captured faithfully within the required accuracy (square-root of sum of squared errors in x,y,z positions).

4 System Level Architecture

Foot-mounted inertial navigation can provide accurate localization for limited operational range and time. Dual foot-mounted systems can increase the accuracy significantly. However, the inertial navigation only provides relative localization and orientation with unbounded errors. For most applications, this is not sufficient. Therefore, the inertial navigation has to be combined with additional information sources in order to provide a position with bounded errors and relative to a relevant coordinate frame. This can essentially be done in three different ways. First, the INS may be combined with additional sensors providing information about the environment. Secondly, ranging to other agents may be used to perform cooperative localization. Thirdly, additional motion constraining information (maps) and assumptions may be added. Potentially, the methods may also be combined. In the following subsections we review the different methods and discuss their implications.

4.1 *Additional sensors*

The most straight-forward way of mitigating the errors and relating the inertial navigation to a global reference frame is by combining it with additional sensors. The potential additional sensors can be divided into infrastructure dependent, e.g. GPS receivers,[12,13] RFID readers,[14] and beacons;[15] and infrastructure independent, e.g. magnetometers,[16,13] radar,[17] barometers[18] and imaging sensors. An example setup with a camera can be seen in Fig. 5. The camera may represent any of the mentioned sensors.

The infrastructure dependent sensors provide bounded errors, unlike INS where errors grow over time. The drawback of infrastructure dependent sensors is that, due to limited coverage area, blind spots occur, where the signals are not available to compute positions. However, the advantage of the foot-mounted inertial navigation system is that it can address the issue of blind spots, effectively. But, infrastructure independent sensors require prior or acquired knowledge about the environment and will not relate the inertial navigation to a global coordinate frame but only constrain certain dimensions (for example, north-direction from magnetometer and height above sea-level from barometer). From a system perspective, since they do not require any infrastructure, they are inexpensive to use and only add a minimum number of dependencies. Overall, adding additional sensors has minimal system implications and since all information is local to the agent, the main challenge is that of statistical conditioning, of the agent's position and heading, on the sensor measurements.

4.2 *Cooperative localization*

In many scenarios, depending on existing infrastructure is undesirable and relying on other extroceptive sensors is insufficient. However, for interaction between multiple agents, only a common rather than a global coordinate frame is necessary. In this case, the positions of the agents may be related to each other by cooperative localization. Cooperative localization is performed by measuring and distributing quantities related to positions of multiple agents with the most common type of measurement being inter-agent ranging. An example of a system setup is shown in Fig. 9. The cooperative localization has the advantage that only a few assumptions about the environment have to be made and a significantly improved positioning performance may be achieved.[19,20] However, the complexity of the system increases significantly. First of all, communication links between the agents become necessary. Secondly, the problem of estimating individual agents' positions cannot in general be separated and one has to resort to distributed estimation techniques or exploit centralized or partially decentralized processing with obvious disadvantages.

4.3 *Map-aiding and motion models*

Zero-velocity updates can essentially be described as a motion model of the human gait, which made inertial navigation usable for pedestrian localization. However, further assumptions/models about the human motion can be made which in some scenarios can greatly improve the positioning accuracy and relate the inertial navigation to a relevant frame. The most obvious assumption is that humans do not walk through walls. Combined with map information this can be used to bound the position errors and relate the inertial navigation to the coordinate frame of the map (given that the user is known to be located on the map to start with).[21] In general this will require a multi-hypothesis (particle) filter. An illustration of this map-aiding is seen in Fig. 10. A somewhat looser model which can be used if only exterior maps are available is that an agent has a bias to walk parallel to building walls.[22]

Apart from traditional map-aiding, several other motion models which do not rely on external information may be added. Trivial examples include floor-pinning. However, more elaborate models may be added which essentially rely on the assumptions that an agent is more likely to walk where the agent or someone else has walked before.[23] This can be used together with particle filters to position the agent and also to build up maps of the area where the agent moves.[23] Unfortunately, this requires agents to revisit locations for the model to be active.

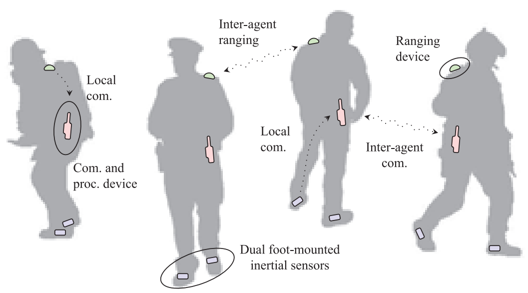


Figure 9: Illustration of cooperative localization setup. Each agent is equipped with dual foot-mounted inertial navigation units and an inter-agent ranging device. In combination, this information can be used to estimate the agents' positions relative to each other and relative to a navigation coordinate frame.

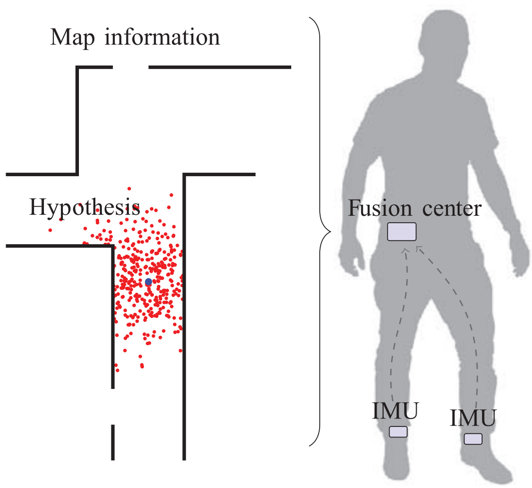


Figure 10: Illustration of map-aiding of the foot-mounted inertial navigation system. Multiple hypotheses of the agent's motion are propagated by the inertial navigation and the hypothesis which passes through walls is pruned and new hypotheses are sampled. Thereby, the map information is included in the localization.

Figure 11: WiFi communication interface for first responder system.

4.4 *Hardware platform and communication interface*

The data from the Openshoe is processed by a hardware platform. It is assumed that there is no local communication infrastructure available at the disaster location. Hence a WiFi virtual private network is used. Fig. 11 indicates a typical configuration where multiple sensor information is transmitted using a WiFi virtual private network involving the command station and the first responders.

Two versions of the prototype have been developed using two different hardware platforms. One of them, developed at IISc uses a BeagleBoard powered by a battery (Fig. 11). The DSP processor and the ARM based processor take data from different sensors and communicate over a WiFi (or 3G) network to the command station. Another version, developed at KTH, uses an Android-based Smartphone instead of the BeagleBoard.

4.5 *Video data transmission*

In order to view the scene a First Responder sees, a helmet mounted camera is used. The video data is then compressed in real-time using the DSP processor on the processing platform and sent to the command station using the prevailing wireless communication interface, which is typically a WiFi network or a 3G network. The challenge in video data transmission is to ensure good video quality at minimum data rates. A simple solution to reduce data traffic is to utilize the redundancy in video and send packets without a re-transmission protocol. This ensures reasonable quality with minimum latency. The DSP processor board will take the video data from the camera and compress it in real-time using a dedicated DSP processor at the appropriate frame rate for onward transmission using RTP protocol.[24] Future schemes will work on creating ad-hoc networks where each first responder's communication interface can also work as a relay of data from other neighbouring first responders.

4.6 *Requirements on test site*

A test site for full scale experiments requires not only a suitable construction of the multi-story location, but also a controllable radio frequency environment to emulate harsh environments that arise in for example an industry building under fire. Further, practical aspects have to be considered, like direct outdoor-indoor access for evaluation of seamless transfer from outdoor to indoor scenarios. A pre-installed ground truth positioning and navigation system is required for performance evaluations. An easily accessible geographical location is also of utmost importance once professional end-users like fire fighters are involved, to guarantee their availability on short notice for urgent missions.

5 Summary & Conclusions

5.1 *Achievements*

The joint Indo-Swedish activity has resulted in the Openshoe project where the design of the INS-based shoe is made available for anyone to replicate. The two groups at IISc and KTH have worked together to build a suite of signal processing algorithms and also developed the prototype on multiple hardware platforms like the Linux-based BeagleBoard and Android-based Smartphone platforms. The current system delivers an average position accuracy of about 2 m and work is in progress to reduce the error.

5.2 *Outlook*

There is a continuous rapid development of MEMS technology, with a regular flow of new IMUs on the market, implying smaller form factors and reduced cost which in turn leads to shoe-free implementations like the sole illustrated in Fig. 12. This trend enables mass market applications like gait stability analysis by gait feature extraction and real-time tracking. Forecasts indicate the percentage of population which is 65 years or older is likely to grow rapidly to 10.4% of 7.9 Billion in year 2025 (with some 110 million elderly persons in India, alone). Hence, there is a need to develop physical activity monitoring and diagnostic tools for assessing the mobility and motor skills of elderly persons and, if this falls below a critical threshold, design and test a variety of assistive solutions for helping elderly persons maintain or even improve levels of physical activity for full, active and independent lives. This

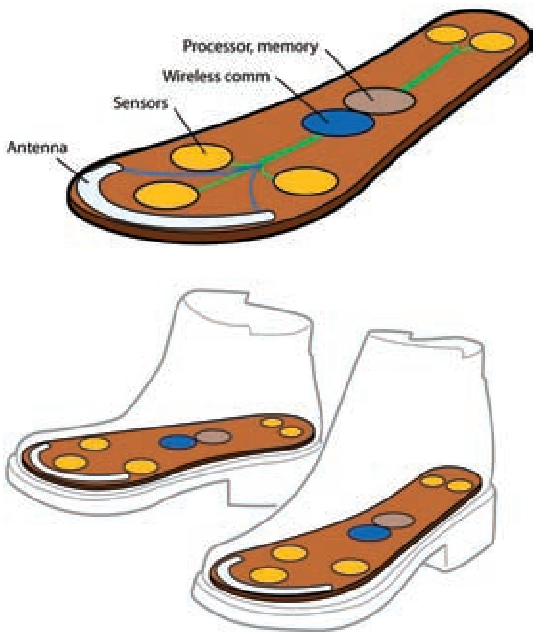


Figure 12: Concept of sensor sole for signal analysis and classification of different gaits, body movements and localization information.

involves developing and fitting inertial motion tracking and gait analysis technologies for long-term monitoring at home, which is subject to further studies.

Acknowledgements

The authors would like to acknowledge the valuable contribution of Prof. Bharadwaj Amrutur, Anand Satpute, Girisha R. Shetty, Department of ECE, IISc in terms of their significant technical inputs to this activity. The financial support of DST, India and VINNOVA, Sweden is gratefully acknowledged.

Received 6 August 2013.

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