SLAC: 3D Localization of Human Based on Kinetic Human Movement Capture

Qilong Yuan, I-Ming Chen, Senior Member, IEEE, Shang Ping Lee

Abstract—This article introduces a method called SLAC (Simultaneous Localization And Capture) to track the spatial location of a human using wearable inertia sensors without additional external assistive global sensing device (e.g., camera, ultrasound, IR, etc.) The method uses multiple wearable inertia sensors to determine the orientation of the body segments and lower limb joint motions. At the same time, based on human kinematics and locomotion phase detection, the spatial position and trajectory of a reference point on the body can be determined. Preliminary experimental study has shown that the position error of SLAC can be controlled stairs within less than 2% error of the total distance travelled for a person to walk around a rectangle on the floor and climb up and down stairs. A benchmark study on the accuracy of SLAC was carried out using the camera-based Motion Analysis® system. The localization data obtained from SLAC tally well with that from the commercial system. The positioning accuracy obtained from SLAC is at least an order of magnitude better than that of GPS. Since the sensors can be worn on the human at any time and any place, this method has no restriction to indoor and outdoor applications and is complimentary to GPS applications.

I. INTRODUCTION

Tracking the location of human has always been a very important problem and challenge for many indoor and outdoor applications. For outdoor applications, GPS is a much matured technology that can give the spatial location of the subject within a maximal accuracy of 10m. However, for indoor human tracking with 3D locations, there are still many technology hurdles to overcome due to the complexity of indoor environments, the constant changing setting (e.g., the moving objects or people), and interference. The main uses for indoor human tracking are in medicine, healthcare, business logistics, manufacturing, commercial advertisement, and possibly entertainment. People may want to know the whereabouts of a particular subject or a group of subjects for a certain time period or to continuously monitor the activities of the subject for detail analysis.

In this article, we introduce a new method to track the spatial location of a human in daily life environments. Since the application scenario is in the daily-life environment, the use of sensing fixtures, such as camera, ultrasonic device, UWB radar, should be avoided or minimized in order to keep the system cost at a manageable level. Most importantly, the positioning accuracy should be within meter level for human perception of the scale of the environment.

The proposed 3D human localization method, SLAC (Simultaneous Localization And Capture), is based on the fact that walking requires human feet in contact with the ground. Thus, by identifying the contact state of the human foot on the ground and capturing the lower limb postures and movements at the same time and continuously, one should be able to know the trajectory of a reference point on the human body over a period of time. Because the body postures and movements contain 3D data, the localization results in 3D position of the subject. The concept of SLAC is illustrated in Figure 1. In the Initial Phase 1, SLAC register the global position \( P_0(0) \) of a reference point on the human body (root) from some fixed global positioning sensing device, and also calibrate the body posture. When the subject starts to move and walk in Phase 2, the inertia sensors begin to capture lower limb postures and compute the trajectory of the root point. As the human continues to walk, the foot contact patterns are captured and identified by the foot sensors in Phase 3. Together with continuous motion capture, the kinematic parameters of human location can be estimated. Subsequently in Phase 4, SLAC repeats in the periodic human walking motion. Variations in the walking patterns can be captured and handled by SLAC in real time to give immediate positioning information of the subject.

Fig. 1. Working principle of SLAC

For the actual capturing and identifying the foot contact phases in SLAC, we propose to use miniature inertia measurement units (IMU) that can detect the spatial orientation of the object and other kinetic parameters. The human postures and movements can be captured by using a number of such IMUs worn on the body. Off-the-shelf contact sensors and the controller are specially fabricated and built into the in-sole of the shoes to identify the foot contacts.

During the last decade, some researchers tried to solve the human walking localization problem [1, 2, 3, 6]. Foxlin built a

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Shoe-Mounted pedestrian tracking system using IMUs [1]. He proposes a ZUPTs method to prevent double integration of acceleration from drifting. However, the accuracy is affected by walking speed and walking pattern. Dead-reckoning technology uses patterns of accelerations for human walking to roughly estimate the walking speed and distance [3]. However, as the walking patterns are different from person to person, the model must be trained for a specific user. Also, it is only suitable for regular even ground walking. The vertical coordinate of the subject cannot be accurately estimated. Woodman proposes a 2.5D indoor user location tracking method based on environmental constraints [2]. However, it is limited in a known surrounding environment. As existing shoe-mounted tracking devices only have coarse location information, it is insufficient to fully understand the posture behavior of a subject most of the time. Most importantly, these devices can only be used for ordinary walking on even terrain. They are not available for variable ground conditions. The proposed SLAC method comes in as a new approach to provide 3D position of a subject without such limitations.

II. METHODOLOGY

Figure 2 illustrated the design and workflow of SLAC algorithm. The middle point of the hip is critical for robot motion planning and biomechanics, and is usually considered as the root point for visualization/animation hierarchy. Therefore, we choose this point as the reference root point for localization, as shown in Figure 6.

![Fig. 2. Algorithm Flow Chart of SLAC](image)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Start Frame</th>
<th>End Frame</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{w2w}$</td>
<td>Pelvis Body</td>
<td>Pelvis Sensor</td>
</tr>
<tr>
<td>$R_{w2b}$</td>
<td>Trunk Body</td>
<td>Trunk Sensor</td>
</tr>
<tr>
<td>$R_{v2w}$</td>
<td>Trunk Body</td>
<td>Pelvis Body</td>
</tr>
<tr>
<td>$R_{v2s}$</td>
<td>Trunk Sensor</td>
<td>Pelvis Sensor</td>
</tr>
<tr>
<td>$R_{i2w}$</td>
<td>World</td>
<td>Pelvis Sensor</td>
</tr>
<tr>
<td>$R_{i2s}$</td>
<td>World</td>
<td>The i-th Sensor</td>
</tr>
<tr>
<td>$T_{v2tL}$</td>
<td>Right (Left) Thigh</td>
<td>Root</td>
</tr>
<tr>
<td>$T_{v2sL}$</td>
<td>Right (Left) Shank</td>
<td>Right (Left) Thigh</td>
</tr>
<tr>
<td>$T_{v2sF}$</td>
<td>Right (Left) Foot</td>
<td>Right (Left) Shank</td>
</tr>
<tr>
<td>$T_{w2s}$</td>
<td>World</td>
<td>Right (Left) Foot</td>
</tr>
<tr>
<td>$T_{w2w}$</td>
<td>World</td>
<td>Root</td>
</tr>
</tbody>
</table>

The rotation matrix $R_{w2w}$ ($T_{w2w}$) represents orientation (homogenous transformation) of the end frame X with respect to the start frame Y.

A. Definition of frames

To describe the motion of the subject, a set of coordinate systems are defined. The world frame ($F_w$), a reference global frame for the global 3D motion of the subject) is defined such that X-axis points north, Y-axis points east, and Z-axis points downward. As the root point is continuously tracked in SLAC, we define the pelvis body frame as the root frame whose origin is at the root point. Therefore, the position and bearing of the subject is captured by tracking this frame.

To represent the motion of the body segments, we define a body frame for each segment. For convenience, all the body coordinate systems are chosen such that X-axis points forward, Z-axis points downward when the subject stand in the standard posture for calibration, and Y-axis is determined by Z and X. The origins of body frames are chosen basing on the predetermined skeleton of the subject. Each IMU sensor also needs its own body sensor frame whose orientations are tracked directly from sensor outputs. All notions of the frames are defined in Table I.

![Fig. 3. Calibration. Step one: Sand instand posture. Step two: Stoop down](image)

**B. Calibration of sensor orientations in body frames**

To get the initial location and bearing of the subject and the mapping between body frames and sensor frames, we need a calibration process at the beginning of the SLAC. The Calibration consists of two steps:

**Step 1:** Put a board with footprints at the initial location on the even ground and let the two feet match the foot prints. Then, keep standing straight (initial standard posture) for 10s during which the posture will be saved in the computer.

**Step 2:** Stoop down as shown in Figure 3 and keep the posture for 10s for the computer to save the stoop posture.

During the two steps the upper body of the subject only rotates around the Y-axis of his waist which is also the Y-axis of the body frame. Thus, this axis can be identified by extracting the screw axis of the motion of the upper body. Let $R_{sid}$ represent the rotation matrix of the upper body in the standstill posture with respect to the world frame $F_w$, $R_{sxp}$ represent the rotation matrix of the upper body in the stoop posture with respect to $F_w$. The relative rotation matrix from the standstill posture to the stoop posture becomes:

$$R_{sid2sxp} = R_{sid}^{-1}R_{sxp}$$  \hspace{1cm} (1)

where the direction of screw axis in world frame can be presented as follows,

$$v_{sid} = R_{sid}v_{sid} = R_{sid}Sc(R_{sid2sxp}) = (x_s, y_s, z_s)$$  \hspace{1cm} (2)

where: $Sc(R_{sid2sxp})$ is a function extracting the screw axis of $R_{sid2sxp}$ in the local frame. It is calculated as follow [16].
Here, \( S = R_{n_{2}n_{2}p_{2}p_{2}} - R_{n_{2}n_{2}p_{2}p_{2}} \). Here, \( S \) is a skew-symmetric matrix.

The normalized rotation axis in the local body frame is given by:

\[
p_{\text{rel}} = \frac{1}{\sqrt{s_1^2 + s_2^2 + s_3^2}} [s_1, s_2, s_3]^T
\]

(3)

Now pre-multiply \( R_{\text{std}} \) to transform the axis into the global frame. At the initialization phase, the angular displacement between the root frame and the world frame contains only the bearing along the \( Z \)-axis of \( F_w \). Thus, we can determine the bearing of the subject by calculating the angle between the \( Y \)-axes of the two frames given by the following equation.

\[
\Phi = -\arctan(2(x_{y}, y_{x}))
\]

(4)

The rotation matrix from the world frame to the body frame can be written as \( R_{\text{Body}} = R_{\text{Body}}(\Phi) \).

At the initial standard posture, the body segment frames are parallel to the body frame. As a result, the mapping from each segment frame to its corresponding sensor frame can be determined using the recorded standard posture data and \( R_{\text{Body}} \). Taking the rotation matrix from the pelvis frame to its sensor frame as an example:

\[
R_{\text{PelB}2\text{S}} = R_{\text{PelB}2\text{S}} \cdot R_{\text{PelB}2\text{B}} \cdot R_{\text{B}2\text{S}}
\]

(5)

Here, in the standard posture: \( R_{\text{PelB}2\text{B}} = R_{\text{PelB}2\text{B}} \). For other body segments, the mappings are determined similarly. The mapping matrices can be considered as constant and used for joint motion update before a second calibration procedure is carried out.

### C. Joint motion tracking

Based on the frame definition and the calibration results, the motion of body joints can be captured. The methodology is given below, taking the waist joint motion calculation as an example:

\[
R_{\text{PelB}2\text{S}} = R_{\text{PelB}2\text{B}} \cdot R_{\text{PelB}2\text{B}} \cdot R_{\text{B}2\text{S}}
\]

(6)

\( R_{\text{PelB}2\text{S}} \) is updated using:

\[
R_{\text{PelB}2\text{S}} = R_{\text{PelB}2\text{B}} \cdot R_{\text{PelB}2\text{B}} \cdot R_{\text{B}2\text{S}}
\]

(7)

Here \( R_{\text{PelB}2\text{B}} \) and \( R_{\text{PelB}2\text{B}} \) are updated directly from the sensor output, ZYX Euler angles: yaw \( \alpha \), pitch \( \beta \) and roll \( \gamma \) as:

\[
R_{\text{PelB}2\text{S}} = f(\alpha, \beta, \gamma) = \text{rotz}(\alpha) \cdot \text{roty}(\beta) \cdot \text{rotx}(\gamma)
\]

\( R_{\text{PelB}2\text{B}} \) and \( R_{\text{PelB}2\text{B}} \) are considered as constant matrices after the sensors are tightly mounted onto the body regardless of the slight motion between the sensors and the body segments. Note that a study on the effect of skin movement to the wearable IMU reading had been conducted in the lab showing that the skin/muscle movement effect can be neglected with proper mountings locations.

### D. Root location update

To localize the subject in the surroundings, the 3D trajectory of the root and joint motions of the subject need to be tracked. In human walking, the right and left foot contact with the ground step by step alternatively. Therefore, after initializing the postures of both feet and the root, the root location and the swinging foot location can be updated from the location of the supporting foot, the body joint motions and physical body parameters of the subject.

The body dimensional parameters are determined by measuring the lengths of the subject’s body segments and can be modified more precisely for more accurate localization. The frames are shown in Figure 5. For different contact conditions, the root locations are updated differently. Details are explained in Section II.E.

When the right foot is determined as the contact foot, the root location and the left foot locations are calculated based on right foot. Thus:

\[
T_{\text{W}2\text{Root}} = T_{\text{W}2\text{Root}} \cdot T_{\text{W}2\text{B}} \cdot T_{\text{B}2\text{B}} \cdot T_{\text{B}2\text{S}} \cdot T_{\text{S}2\text{Root}}
\]

(8)

\[
T_{\text{W}2\text{LF}} = T_{\text{W}2\text{Root}} \cdot T_{\text{W}2\text{B}} \cdot T_{\text{B}2\text{B}} \cdot T_{\text{B}2\text{S}} \cdot T_{\text{S}2\text{Root}} \cdot T_{\text{S}2\text{LSh}} \cdot T_{\text{LSh}2\text{LF}}
\]

(9)

When the left foot is in the support phase, the root locations are calculated based on the left foot posture similarly.

The transformation between adjacent frames is defined by \( T_{i+1} \). The joint motions present the rotation part \( R_{i+1} \), while the physical dimensions determine the translation part \( P_{i+1} \),

\[
T_{i} = \begin{bmatrix} R_{i} & P_{i} \\ 0 & 1 \end{bmatrix}
\]

(12)

### E. Contact phase detection

The objective of phase detection is to detect the contact event between feet and ground. Although normal continuous walking patterns of human include not only the support and swing phase but also the heel-contact and toe-off phases for each foot, it has been reported that the time for the heel-contact and toe-off phases are very short [12,13]. Thus, in this work we mainly detect the support phase as contact phase and consider the rest phases as the Non-contact phases. The phase detection is based on the data of accelerations along the \( Z \)-axis \( a_{Z}^{C} \) (Global Frame) and the angular velocity along
the Y-axis $\alpha_y^0$ (Foot Frame) of each foot, and the force sensor output. When one foot is in the supporting phase, $a_z^c$ and $\omega_x^c$ are near trivial and the foot should be in contact with the ground. Therefore, we detect the contact condition of the foot by combining these data together. A fuzzy membership is used to identify different contact phases. The input are $a_z^c$ and $\omega_x^c$, and their fuzzy membership functions $\mu_1(\omega_x^c)$ and $\mu_2(\omega_x^c)$ are defined as:

$$\mu_i(\omega_x^c, a_z^c) = \frac{\beta_i \mu(a_z^c) + \beta_i \mu_2(a_z^c)}{\beta_i + \beta_i}$$  \hspace{1cm} (13)

Here $a_z, \omega_x$ are specified thresholds, and $\beta_1, \beta_2$ are the weights of the two inputs respectively. In this work, these parameters are chosen based on trial-and-error as follows:

$\alpha_z = 0.3 m/s, \omega_x = 0.3 rad/s, \beta_1 = 0.4, \beta_2 = 0.6, \mu_1 = 0.75$

If $\mu_1(a_z^c, \omega_x^c) \geq \mu_r$, and at least one FSR is in contact condition, the phase is considered as Contact Phase. Otherwise, we consider the phase as Non-Contact Phase.

For normal walking and climbing, there is always contact. If both the right and the left feet are in the contact phase, the root location is calculated combining the results from both feet. If only one foot is in the contact phase, the root location is calculated from the supporting foot.

### III. System Device

The system is made up of eight wireless IMU sensors on body and a pair of wireless in-sole device with force sensors. Their outputs are wirelessly sent to the PC through USB receivers and Bluetooth modules. Therefore, there is little constraint of the human body from the system device. The subjects can move freely and continuously within a large area during which the posture and location are captured on PC using sensor data and SLAC in real time.

### A. Spatial Orientation Tracking Device

As shown in Figure 8, the eight IMUs on the body are placed as following: one on the trunk, one on the pelvis, and three for each leg attaching one thigh, shank and foot respectively. In order to minimize the skin motion effect, the IMUs are mounted on the limbs close to the bones where skin movement is negligible. IMU parameters can be found in [4].

### B. Contact phase detection device

In order to detect the foot contact information on the ground, four force sensing resistors (FSR) with the controller are designed and fabricated under the insole of the shoes. When the FSR sensor is pressed on the surface, the resistance will decrease. Thus, we can detect the contact condition of the foot through the output voltage as shown in Figure 9.

The system communicates wirelessly with the PC through Bluetooth. Together with the angular velocities and accelerations of the foot, the foot contact can be detected more accurately. The subject’s location can be updated consequently.

### IV. Experiment and Results

In order to verify the capability of SLAC, and enhance the accuracy of the system, several experiments are conducted. All these experiments are carried out in areas away from magnetic resources to avoid the interference with IMUs.

### A. System calibration with stationary references

To study the possible overall localization errors in the system, a calibration experiment based on known stationary location in a prescribed environment is carried out. The experiment uses a set of standard footprints on a cardboard with pre-determined dimensions. [The distance between two adjacent footprints is 20 cm in both X (forward) and Y (sideward) directions.] The subject is required to stand on theses footprints and keep stationary for a while. Then the IMUs will capture the lower limb postures and compute the locations of the right ankle which is used to present the location of right foot. The result of this experiment reveals the overall sensing errors in a controlled condition and thus, can be used to compensate SLAC in real scenario.

First, the subject puts his left foot on a specified footprint. Then, he puts his right foot on a set of specified points and keeps stationary for 5 seconds, as shown in Figure 10.

![Fig. 8. Location of IMUs on the body](image)

![Fig. 9. The insole and the circuit diagram for FSR](image)

![Fig. 10. Static Localization Testing](image)

![Fig. 11. Stationary posture calibration data on the XY-Plane](image)
The dimensions of the human skeleton are used to calculate the captured location of the right foot. The locations of the root point projected onto the XY-plane are shown in Figure 11. The curve in red color represents the trajectory of the right foot during the footprint matching. The captured foot location is shown where the point density is high as the foot holds for 5 to 10 seconds. The result shows good accuracy with error within 1 cm in the normal walking range.

Note that the captured root position in the Z-direction is not as accurate as in the XY-plane. The curve in blue in Figure 12 shows the foot trajectory along the Z-axis. Figure 15 indicates that there is an offset along the Z-direction which is proportional to the direction of travel. Further experiments also show that the offset along the Z-direction is proportional to the distance of travel. Thus, the captured walking motion on the even ground looks like climbing up a slope as the captured vertical position of the subject increases with time. Fortunately, it can be modeled as a linear function of the accumulated distance of travel \( \sum_{j=1}^{n} r_{foot}^{x} \ac_{root}^{y} \). where \( k_{ac} \) is determined during the stationary system calibration experiment before using SLAC for motion studies. \( l_{ac} \) can be calculated from:

\[
l_{ac} = \sum_{j=1}^{n} r_{foot}^{x} \ac_{root}^{y}
\]

where \( r_{foot} \) represents the vector from the rear foot to the front foot, \( \ac_{root}^{y} \) represents the globe coordinate of the X-axis of the root frame, and \( n \) represent the total number of steps.

With such a proportional system error model replacing (Z) values with (Z-e), the vertical displacement in SLAC can be captured correctly. The curve in red in Figure 12 shows the accurate Z coordinate of the foot after error elimination. This proportional error model becomes part of the system calibration and only needs to be applied once for the subject conducting as many localization experiments including walking up and down the stairs. The results of the following localization experiments show that this model is effective in maintaining good accuracy in vertical direction.

**B. Self-localization for walking along a rectangle**

To verify the localization accuracy of the system, walking around a closed trajectory - the border of a 3 m by 2.8 m rectangle is tested, and. The subject starts from a corner of the rectangle, walks around the rectangle and then returns to the starting point matching the marked starting footprint.

The walking speed is about 0.8 m/s. The captured trajectories of the root and the feet in the XY-Plane are shown in Figure 13. The black and blue dash line presents the trajectory of right and left foot respectively. The arrows present the bearing orientation. The red line provides the trajectory of the root in the XY-Plane. As the subject cannot exactly follow the rectangle during walking, the actual motion trajectory is different from the rectangle in green color. Even so, the error for a single trip is still within 15 cm, less than 2% of the total distance of travel (about 12 m).

**C. Localization with 3D motions (up & down stairs)**

To show the capability of 3D localization in SLAC, a stair climbing experiment is conducted to localize the subject. In this experiment, the subject first went upstairs on stairs and then downstairs to the original position.

The trajectory of the feet and the estimated center of gravity (CG) for climbing up stairs are shown in Figure 18. The estimated CG is calculated from the captured postures (exclude arm motion). We can see that the subject climbed one stair for each step. The approximate CG trajectory forms shapes similar to that of the stairs.

For many applications such as medical monitoring and robot motion planning, the postures of the subjects are also important. Figure 15 shows the lower limb movements in the stair climbing experiment. The behavior of the subject can be identified from his posture. Details of the climbing stair motion are provided in the attached video “UP and Down Stairs.mpg”. As SLAC tracks the location of the root together with the postures, it provides additional information such as estimation of CG and trajectories of body joints which help for motion planning and medical studies.
D. Benchmark study with Motion Analysis®

Motion Analysis® is a commercial optical motion capture system used in many biomedical and entertainment applications. In this experiment, it is used as a benchmark to compare with the proposed SLAC method. The system used in our benchmark study consists of 8 cameras. In this study, the subject wears the necessary reflective markers and IMUs together as shown in Figure 16. The subject walks at a speed of 0.8m/s on a flat platform forming a rectangle. The walking motion is captured by the two systems at the same time.

![Fig. 16 IMU and MOCAP markers setup for comparison](image)

The root trajectories from the two systems are compared after the trajectories are presented in the same world coordinate frame.

![Fig. 17 Localization results of the two systems](image)

The comparison of the two localization results is shown in Figure 17. The difference between the two systems is within 10cm most of the time. Therefore, the accuracy of the SLAC method is verified.

V. Conclusions

In this paper, a new human 3D localization method, SLAC, based on human body kinematics and locomotion phase detection is proposed. The complete system includes eight IMUs and one pair of FSR mounted insole device. Preliminary experiments results show good accuracy in even-ground walking and stair climbing. An error cancelation method is proposed to eliminate the error in vertical direction. Overall speaking, the accuracy of this system is within 2% of the distance of travel.

Currently, SLAC can handle motions with distinctive contact conditions, like casual and regular walking and strolling. Research is underway for localization of the human in fast movements with unstable contact states, such as fast walking, running and jumping.

As the accuracy of SLAC is at least an order of magnitude better than that of GPS, it is possible to integrate it with GPS or other absolute positioning systems to provide multi-resolution user-based positioning for both indoor and outdoor environments. Because the design of the SLAC uses body worn sensors to capture postures as well as the locations, the existing Wi-Fi infrastructure in many homes and workplaces can also be used to communicate with the body worn sensors to conduct online multi-user tracking and monitoring in a daily living environment.

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