Magnetic and Inertial Orientation Tracking for Inserting Humans into Networked Synthetic Environment

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Abstract: This study demonstrates the new technology that overcomes the limitations of motion tracking technologies currently in use. The technology is capable of providing wide area tracking of multiple users for synthetic environment and augment reality applications. This system makes a significant step toward total immersion of users in a networked synthetic environment by allowing them to interface with it using their natural bodies. Orientation can be determined without the aid of a generated source using nine axis Magnetic, Angular Rate and Gravity sensor unit containing three orthogonally mounted angular rate sensors, three orthogonal accelerometers and three orthogonal magnetometers. Primarily this study involves the development of a prototype MARG Sensors tracking system including innovative calibration and angle tracking software. An examination of this implementation demonstrates the feasibility of a hybrid motion tracking system for networked synthetic environments. Mathematical analysis, a computer simulation and physical experiments are used to validate the correctness of the complementary filter algorithm as well as human body model. Experimental results show the effectiveness of the tracking system.

Key words: Networking, quaternion, complementary filtering, and virtual environment

INTRODUCTION

Fully developed networked synthetic environments stand to revolutionize the fields of education, training, business, retailing and entertainment. They will fundamentally alter our societies and the way in which mankind views the world. In the educational field, synthetic environments will offer the ultimate in hands-on and visualization of difficult concepts. They will allow training to transpire in a place much like that in which the skills being practiced will be used without exposure to possible hazards and at less cost. In the workplace, employees will be able to work side by side even though they may be physically separated by hundreds or even thousands of miles. Using synthetic environments, corporations will obtain a safe, economical and efficient method of testing new concepts and systems. The power of the synthetic environment lies in its ability to immerse users in a different world. The more complete the immersion, the more effective the synthetic environment[1,2].

For complete immersion, the user should sense and interact with the synthetic environment in the same manner in which interaction with the natural world takes place. Interaction in the natural world results from body motion. Information regarding the surrounding environment is obtained through the five senses. Changes in body posture and position directly affect what is seen, heard, felt and smelled. The parameters sensed in the environment are altered and manipulated by the actions of the body. Thus, in order for a user to interact with a synthetic environment in a natural way and have the synthetic environment present appropriate information to the senses, it is imperative that data regarding body motion and posture be obtained. Body posture and location data are also needed in multi-user environments to drive the animation of avatars which represent the actions of users of the environment to each other[3].

The development of micro machined magnetometers and inertial sensors over the last few years makes it possible to determine orientation based on the passive measurement of physical quantities which are directly related to the motion and orientation of a rigid body to which they are attached. The "sourceless" nature of inertial and magnetic orientation tracking makes possible a full body posture tracking system that avoids the problems associated with current technologies and ultimately allows tracking over a virtually unlimited area. Each MARG sensor contains three orthogonal angular rate sensors, three orthogonal linear accelerometers and three orthogonal magnetometers. Estimation error is

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minimized using Gauss-Newton iteration. Drift is corrected continuously without any requirement for still periods. Body posture is determined by estimating individual limb segment orientations through the attachment of MARG sensors. The orientation estimates are used to animate a simple human model or avatar in real-time. The model directly accepts limb segment orientations in quaternion form relative to an Earth-fixed reference frame. Simple calibration procedures determine sensor scale factors and null points for the MARG sensors as well as account for offsets between the sensors coordinate frames and the frames associated with the limb segments to which they are attached. To track the posture of the entire human body, approximately fifteen nine-axis units would be required. One sensor would be attached to each limb segment to be tracked. The exact number of sensors needed would depend upon the desired motion tracking detail to be captured. Three such sensors used in the system were described[4-7].

QUATERNION BASED COMPLEMENTARY ATTITUDE FILTER

The complementary quaternion based attitude estimation filter block diagram is shown in Fig:1. The filter inputs are from a three axis angular rate sensor (p, q, r), a three-axis accelerometer (h1,h2, h3) and a three-axis magnetometer (b1, b2 , b3). Its output is a quaternion representation of the orientation of the tracked object[8]. Noiseless, unbiased rate sensor data could be processed to obtain a rate quaternion

$$\dot{q} = \frac{1}{2} q \otimes (0pqr) = \frac{1}{2} q \otimes_B \omega \qquad (1)$$

Where, q is a quaternion representing the current orientation, the indicated product is a quaternion product and the superscript B means measured in the body reference frame. Single integration of q would produce a quaternion, which describes orientation. However, in an environment containing noise and errors, the output of angular rate sensors would tend to drift over time. Thus, rate sensor data can be used to determine orientation only for relatively short periods of time unless this orientation is continuously corrected using complementary data from additional sensors. Gravity and the earth's magnetic field provide two fixed vectors that can be used to determine orientation. Accelerometers measure the combination of forced linear acceleration and the reaction force due to gravity. That is,

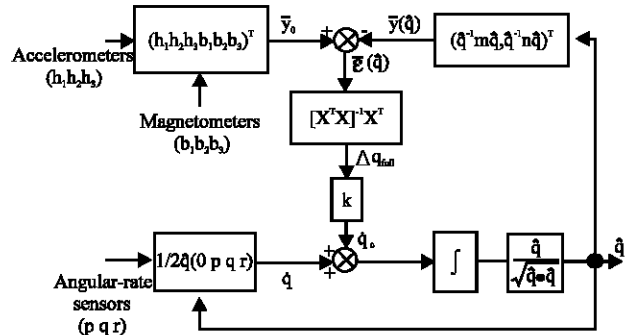$$\vec{a}_{measured} = \vec{a} + \vec{g} \qquad (2)$$

Fig. 1: Quaternion based orientation filter

When averaged over time, an accelerometer triad can return the components of the gravity vector or the local vertical. Determination of this vector allows correction of orientation relative to a vertical axis. Similarly, magnetometers measure the local magnetic field in body coordinates. This information is used to correct rate sensor drift errors in the horizontal plane. Thus, the vectors derived from accelerometer and magnetometer data comprise a second complementary method of determining orientation.

Mathematical analysis-parameter optimization: The complementary sensor input is regarded as a parameter optimization problem with the goal of minimizing modeling error. The three orthogonally mounted accelerometers return an approximation to the local vertical, the unit vector h. The magnetometer returns the direction of the local magnetic field, the unit vector b. These two vector quantities expressed in body coordinates as pure vector quaternion are[9]

$$h=[0 \ h_1 \ h_2 \ h_3] \ b=[0 \ b_1 \ b_2 \ b_3] \qquad (3)$$

Combining the vector parts from Eq. (3) produces a 6 x 1measurement vector

$$y_0=[h_1 \ h_2 \ h_3 \ b_1 \ b_2 \ b_3]^T \qquad (4)$$

Gravity in earth coordinates is always down and can be expressed as the down unit vector in quaternion form as

$$m = [0 \ 0 \ 0 \ 1] \qquad (5)$$

The local magnetic field in earth coordinates, once determined and normalized, can be expressed in quaternion form as

$$n = [0 \ n_1 \ n_2 \ n_3] \qquad (6)$$

Eq. (5) and Eq. (6) are mapped from the earth fixed frame to the body frame through quaternion multiplication

$$h = q^{-1} m q \qquad b = q^{-1} n q \tag{7}$$

Combining the vector parts of Eq. (7) into a single 6 x 1 computed measurement vector produces

$$y(\hat{q}) = [\ h_1 \ \ h_2 \ \ h_3 \ \ b_1 \ \ b_2 \ \ b_3 \ ]^T \tag{8}$$

The difference between the actual measurements and the computed measurement is the modeling error

$$\vec{\varepsilon}(\hat{q}) = {}^{y0^a} - y(\hat{q}) \tag{9}$$

In viewing Eq. (9), note that if in Eq. (7) there is no measurement noise, the minimum difference between the measured and computed values will equal the zero vector. The square of the filter modeling error is termed the criterion function

$$\Phi(q) = e^T(\hat{q}) \vec{\varepsilon}(\hat{q}) \tag{10}$$

The criterion function is minimized using Gauss-Newton iteration in the current version of the filter. This method is based on linearized least squares regression analysis where $y_0^{\ \hat{}}$ is considered a vector of data points and $y(\hat{q})$ is a vector to be fitted to those points. The full correction step to the measured rate quaternion is

$$\Delta q_{full} = [X^T X]^{-1} X^T \varepsilon(\hat{q}) = S^{-1} X^T \varepsilon(\hat{q}) \tag{11}$$

Where the previous estimate for q and the X matrix is is defined as

$$X_{ij} = \left[\frac{\partial y_i}{\partial q_j} \right] \tag{12}$$

Equation 11 treats m and n as if they are perfect measurements of gravity and the local magnetic field. In dealing with data corrupted by noise, a scalar multiplier is used and gravity and the local magnetic field. In dealing with data corrupted by noise, a scalar multiplier is used and

$$\nabla q_{parallel} = \alpha [X^T X]^{-1} X^T \vec{\varepsilon}(\hat{q}) \tag{13}$$

Where

$$\alpha = k \Delta t \tag{14}$$

and k represents the filter gain value. Thus, for discrete time step integration, the next estimate of orientation would be

$$\hat{q}_{n+1} = \hat{q}_{n+k} \Delta t \Delta q_{full} + \dot{q}_{measured} \Delta t \tag{15}$$

Reduced order filter: If $\hat{q}$ is not constrained to unit length as depicted in Fig. 1, a unique solution to the optimization problem no longer exists and the X matrix will not be of full rank[9,7]. In this case the regression matrix

$$S = X^T X \tag{16}$$

will be singular and can not be inverted. A more efficient alternative to the computation of ?results from noting that if

$$\hat{q}_{new} = \Delta q_{full} + \hat{q}_{old} \tag{17}$$

and if both $\hat{q}_{new}$ and $\hat{q}_{old}$ are unit quaternion, then any small Δq_{full} must be orthogonal to $\hat{q}$. That is, the only way to alter a unit vector while maintaining unit length is to rotate it and for small rotations Δq must be tangent to the unit four-dimensional sphere defined by

$$q \otimes q^* = |q|'_2 = 1 \tag{18}$$

Where q^* is the conjugate of q . From the Orthogonal Quaternion Theorem, if p and q are any two quaternion, then p is orthogonal to q if and only if p is the quaternion product of q and a unique vector v (real part equal to zero) where v is given by

$$v = q_{-1} \otimes p \tag{19}$$

Thus, when Gauss-Newton iteration is applied to unit quaternion, it is sufficient to solve for only three unknowns rather than
four as in Eq.11.

Weighed least squares regression: By Fig. 1, the possibility exists of putting greater or less reliance on magnetometer data in comparison to accelerometer data. This could come about because one or the other of these signals could prove to be less accurate (or noisier) than the other. This can be achieved by merely redefining the error vector,

$$\varepsilon(q) = \begin{bmatrix} (y_{01} - yq)_1 \\ (y_{02} - yq)_2 \\ (y_{03} - yq)_3 \\ \rho(y_{04} - y(q)_4) \\ \rho(y_{05} - y(q)_5) \\ \rho(y_{06} - y(q)_6) \end{bmatrix} \qquad (20)$$

Setting $\rho > 1$ emphasizes magnetometer data, while $0 < \rho < 1$ puts greater weight on accelerometer data. This change alters the X matrix by multiplying the last three elements of each column by ρ^2. If a detailed statistical model is available for magnetometer and accelerometer errors for a particular experimental setting then, at least conceptually, the best value for ρ could be obtained from linear estimation theory.

Calibration of sensor: To operate the system properly, it is imperative that the null point and scale factor of each individual component of the MARG sensors be determined prior to commencing limb tracking. Unless the characteristics of the sensors themselves change, calibration need only be accomplished once. However, due to variations in the direction of the local magnetic field vector, better performance is to be expected if the direction of this reference is determined before each tracking session. An individual linear accelerometer can be calibrated by placing it in a vertical position to sense gravity in one direction and then turning it over to sense gravity in the other. Halfway between the readings taken is the null point[10,11].

$$Accel\,null = \frac{accemax + accelmin}{2} \qquad (21)$$

Multiplication of a correct scale factor times the accelerometer output values will result in a product of 1 g in one direction and -1 g in the other. This scale factor can be found using

$$accel\,scale = \frac{(accelunits) \times 2}{accelmax - accelmin} \qquad (22)$$

An obvious method of magnetometer calibration is very similar to that used for accelerometers. Instead of orienting each sensor relative to the gravity vector, each magnetometer would have to be placed in a position in which it can sense the maximum strength of the local magnetic field along both its negative and positive axes. Determination of the null point of an angular rate sensor is achieved by recording and averaging over some time period the output of a static sensor. Scale factors are estimated by integrating the output of angular rate sensor as it is subjected to a known angle of rotation. The scale factor for a rate sensor can therefore be determined following a known rotation using

$$Scale\,fector = \frac{known\,rotation}{estimated\,rotation} \qquad (23)$$

From the above, a MARG sensor can be completely calibrated using a level platform and a simple compass to indicate the direction of the local magnetic field. In this research each sensor was calibrated by placing it in six positions which allowed each accelerometer to sense gravitation acceleration in both the positive and negative directions, subjecting each rate sensor to one or more known rotations and rotating the MARG sensor in a manner such that maximum and minimum local magnetic field readings could be obtained for each magnetometer.

Human body model using quaternion: The vertices of an individual segment of the human model can be described relative to a z-axis down coordinate system that is attached to the inboard end of the segment .If the sensor and limb segment coordinate axes are aligned, the orientation of an individual limb segment could be set by applying to each vertex,
v , the quaternion rotation

$$q_{sensor} \times v \times q^{*}_{sensor} \qquad (24)$$

Where the unit quaternion q is the estimated orientation produced by the filter processing the sensor output. Misalignment between the sensor and limb segment axes can betaken into account by performing an additional fixed rotation using an offset quaternion

$$q_{sensor} \times (offset \times v \times q^{*}_{offset}) q^{*}_{sensor} \qquad (25)$$

to each vertex, where q_{offset} is the offset quaternion for the limb of the vertex. When the human model is in the reference position, the limb segment coordinate axes are aligned with the corresponding. Earth-fixed axes. That is the x-axis for each limb segment points toward the local north, the y-axis points east and the z-axis points down. The offset quaternion for each limb segment can be derived by noting that while the user is in the reference position the equation

$$v = q_{sensor} \times q_{offset} \times v \times q^{*}_{offset} \times q^{*}_{sensor} \qquad (26)$$

holds true. Complete compensation for the way in which all sensors are attached to the limbs of a tracked subject

can therefore be accomplished by simply setting qoffset for each limb segment to the inverse of the associated qsensor while the subject to be tracked is standing in a predetermined reference position. To set the position of an individual limb segment it is necessary to find a vector that describes the location of the inboard end of the limb segment. Once this vector is found the final position of each vertex can be calculated through addition of this vector to the rotated coordinates of each vertex.

System hardware implementation: Inertial/magnetic body tracking system in this research was implemented with several goals in mind. Among these were validations of the quaternion filter algorithm in a physical system, demonstration of the practicality and robustness of inertial and magnetic orientation tracking in real-time and creation of a test-bed for further experiments. Several features are considered imperative if these goals are to be meet[12,13].

Among these are:

- Orientation tracking of any two or more human limb segments using nine-axis MARG sensors
- Sufficient dynamic response and update rate (100 HZ or better) to capture fast human body motions
- Calibration of individual sensors without the use of any specialized equipment
- Simplified human kinematics' model based entirely on quaternion capable of accepting orientation
- parameters relative to an earth fixed reference frame in quaternion form
- Automatic accounting for the peculiarities related to the mounting of a sensor on an associated limb segment.

The prototype system hardware is shown in Fig. 2. Three MARG Sensors are mounted on the body. The analog output from the body is given to three I\O connection boards. The output from each I\O connection board is digitized by an associated A\D converter card .The output from A\D by a 16 bit data acquisition card is connected to the Pentium III processor .All data processing and calculations are performed by software running on this single processor[14].

The sensing system is implemented using C and C++ programming language and the visual C++ advanced compiler. The filter and visual simulation software run on a single standard Pentium III processor. The code follows object oriented and in future modified to Matlab7.0 and is designed, visualized using multimedia techniques that is well suited for a body using multiple sensors.
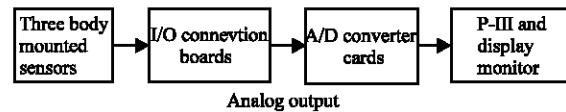

Fig. 2: Prototype body tracking system

Marg sensor: An optimal inertial sensor would have the same size and form factor as a wristwatch. It would include an embedded microprocessor on which the filter algorithm is implemented. The sensor would be have a self-contained power source and would wirelessly transmit orientation data. New sensor components continue to appear on the market. These sensors have capabilities, which are at least equal to and are often superior to those of the proceeding generation and are an order of magnitude smaller in size. Current technology already permits the construction of sensors which are much smaller than either the prototype MARG sensors described here[13,15]. Three prototype MARG sensors were custom built using off-the-shelf, low cost components.

Each sensor package measures 10.1 x 5.5 x 2.5 cm the analog output of the sensor is connected to a breakout header via a thin VGA monitor cable. Output range is 0-5 vdc. The power requirement of the sensors is12 vdc at approximately 50 milli amperes. The primary sensing components are a Crossbow CXL04M3 triaxial accelerometer a Honeywell HMC2003 3-axis magnetometer and three Tokin CG-16D series miniature angular rate sensors mounted in an orthogonal configuration. The individual components are integrated using a single integrated circuit board with the accelerometers mounted separately. Rate sensor output voltage is amplified by a factor of five and filtered to attenuate rate sensor oscillator noise. All three MARG sensors were fabricated by McKinney Technology of Prune dale, California.

Integration of a biased angular rate signal will cause a steady state error in a complementary filter. In earlier body tracking work, the angular rate sensors were bias compensated in software .In order to achieve better system performance, in future systems this correction should be hardware implemented in the rate sensor conditioning circuitry using capacitive coupling. Manufacturer's literature states that HMC1001/2magnetometer saturation occurs due to the influence of a strong magnetic field in excess of 30 gauss, which can cause the polarity of the MR film magnetization to flip[1]. Following such an upset field, a strong restoring magnetic field must be momentarily applied to restore, or set, the sensor characteristics. The effect is commonly referred to as applying a set or reset pulse. The sensors used in this research incorporate a manual set/reset circuit to electrically restore the magnetometers to proper

operation. The purpose of the associated circuit is to set or reset the perm alloy film contained in the individual magnetometers by applying a current pulse of 3-4 amps for approximately 20-50 nsec[16].

PERFORMANCE OF THE SYSTEM

In order to get an initial estimate of the accuracy and robustness of the system under various dynamic and static conditions Quantitative and qualitative experiments were performed. The static experiments related to the stability, convergence properties and accuracy of the orientation estimates produced by the quaternion attitude filter algorithm when processing MARG sensor data. The qualitative experiments examine the performance of the system as a whole in relationship to the goal of robust posture estimation as well as increased drift correction intervals was also investigated[11,18].

Software of the tracking system: Here, the software implements the estimation as well as calibration algorithms which make possible tracking of human body segments using MARG sensors. The object oriented software for this research was written in C++. Estimation and rendering events is window system timer driven at 100 Hz and 25 Hz respectively. The code is single threaded. It runs on a standard 866 MHz Intel Pentium III platform under the Windows 2000 operating system[19].

Static stability of the system: The drift characteristics of the quaternion filter algorithm and the MARG sensor over extended periods were evaluated using static tests. Average total drift is about 1%. During the experiment shown, the filter gain, k (Eq. (14)), was set to unity. Equal weighting was given to both magnetometer and accelerometer data. It is expected that increasing the filter gain to 4.0 would reduce the drift error by a factor of four or to about 0.25 percent. Further experiments indicated that nearly all drift was due to bias in the rate sensors. Experiments are currently underway using improved sensors containing rate-sensor capacitive coupling conditioning circuitry designed to remove these biases.

Dynamic response of the system: Preliminary experiments were conducted to establish the accuracy of the orientation estimates and the dynamic response of the system. These experiments were completed using a Hass rotary tilt table. The preliminary test procedure consisted of repeatedly cycling the sensor through various angles of roll, pitch and yaw at rates ranging from 10 to 30 deg./sec. Figure 3 is a typical result of the dynamic accuracy experiments. The estimates produced by the tracking system are presented in Euler angle form.
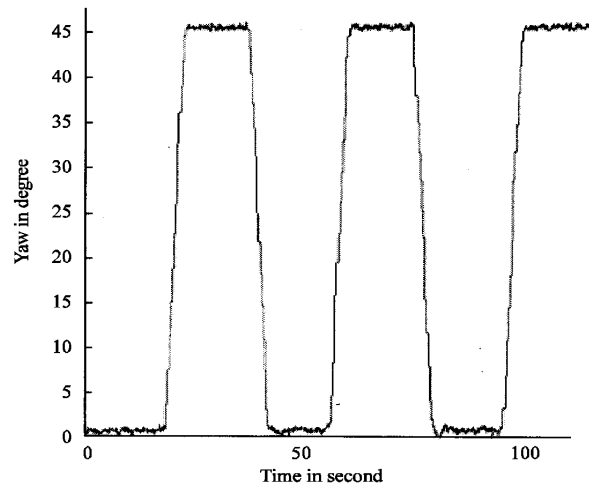

Fig. 3: Excursion for 45 at 10 degree\second

Accuracy was measured to be better than one degree. The overall smoothness of the plot shows excellent dynamic response.

TESTING METHODOLOGY

The sensor block was mounted on the tilt table. The tilt table was programmed to rotate 45 degrees at a rate of 10 degrees per second on every axis for a series of roll, pitch and yaw tests. After initializing the system, three rotations were completed by the tilt table in each test. During each test, a 15 to 20 second stabilization period followed each movement. The scale factors and buffer depth values were adjusted to obtain the desired update rate and accuracy.

Simulation results: The following test result for yaw was obtained using the hardware and software to achieve an update rate of 55 Hz, the graphical representation of orientation was disabled. The update rate with the graphical orientation representation and a single processor was approximately 15 Hz. Estimated orientation was within 1 degree of actual steady orientation throughout the tests. The smoothness of the graphs indicates excellent dynamic response. The small impulses observed at the starting points of motion were hypothesized to be linear acceleration effects exaggerated by a whipping motion of the non- ferrous extension block. It is expected that adjusting the filter scale factors and gain values will reduce this effect and improve the overall accuracy and dynamic response. The transition times observed in the plots are around 4.5-5 seconds as expected for a 10-degree per second rotation rate to 45 degrees. In qualitative tests, the system was able to track all orientations, including those in which pitch equaled 90

degrees; the same orientations normally cause singularities in Euler angle filters. The qualitative tests also show that the system could easily be combined with a simulation program and track motion in real time.

Future work: An optimal inertial sensor would have the same size and form factor as a wristwatch. It would include an embedded microprocessor on which the filter algorithm is implemented as well as an analog to digital converter. The sensor would have a self-contained power source and would wirelessly transmit orientation data. Efforts are currently being made to untether the user of the sensor system by feeding MARG sensor data to a wearable computer. Bluetooth technology[9] is being investigated as a means to create a completely wireless sensor. Filter research has continued with the development of an extended Kalman Filter for real-time estimation of rigid body orientation]. Non-real-time static and dynamic testing of the filter has been performed with synthetic data and real sensor data. In addition, a more efficient formulation of the X matrix is currently being evaluated through simulation. This new derivation will have particular significance as the quaternion filter algorithm is implemented on microprocessors contained within the sensors .The ultimate goal of this project is to insert humans into a networked virtual environment. A network of 15 MARG sensors will track body posture. In order to accurately place the of the user's avatar in the virtual environment, it will be necessary to know body location as well as the posture of the body. To achieve this, the position of one body limb segment must be tracked. Although several technical challenges exist, RF positioning is still seen as the technology which will best complement the source less capabilities of inertial/magnetic sensing and enable tracking of a multiple users over a wide area. While indoor tracking of this type is still under development, currently available differential GPS may provide adequate position tracking for some outdoor applications.

CONCLUSION

The technology is based on the use of inertial/magnetic sensors to independently determine the orientation of each link in the rigid body. Though the primary application described here was motion capture for inserting humans into networked virtual environments, inertial/magnetic orientation tracking could be applied to a broad range of problems which require tracking of an articulated structure without being continuously dependent upon an artificially generated source. At the core of the system is an efficient complementary filter, which uses a quaternion representation of orientation.

The filter processes data from MARG sensors. The implemented system tracks human limb segments accurately with a 100 Hz update rate. Experimental results demonstrate that inertial/magnetic orientation estimation is a practical method of tracking human body posture. With additional sensors, the architecture produced could be easily scaled for full body tracking. This new technology overcomes the limitations of motion tracking technologies currently in use. It is potentially capable of providing wide area tracking of multiple users for synthetic environments and augmented reality applications.

ACKNOWLEDGEMENT

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