Hybrid Tracking of Human Operators using IMU/UWB Data Fusion by a Kalman Filter

J. A. Corrales, F. A. Candelas and F. Torres
Automatics, Robotics and Computer Vision Group.
Physics, Systems Engineering and Signal Theory Department, University of Alicante.
03690 San Vicente del Raspeig, Alicante, Spain.
+34 96 590 94 91
[jcorrales, Francisco.Candelas, Fernando.Torres]@ua.es

ABSTRACT
The precise localization of human operators in robotic workplaces is an important requirement to be satisfied in order to develop human-robot interaction tasks. Human tracking provides not only safety for human operators, but also context information for intelligent human-robot collaboration. This paper evaluates an inertial motion capture system which registers full-body movements of an user in a robotic manipulator workplace. However, the presence of errors in the global translational measurements returned by this system has led to the need of using another localization system, based on Ultra-WideBand (UWB) technology. A Kalman filter fusion algorithm which combines the measurements of these systems is developed. This algorithm unifies the advantages of both technologies: high data rates from the motion capture system and global translational precision from the UWB localization system. The developed hybrid system not only tracks the movements of all limbs of the user as previous motion capture systems, but is also able to position precisely the user in the environment.

Categories and Subject Descriptors
I.2.9 [**Artificial Intelligence**]: Robotics – *operator interfaces, sensors.*

General Terms
Algorithms, Measurement, Experimentation, Human Factors.

Keywords
Motion capture, inertial sensors, UWB, human tracking and monitoring, indoor location, data fusion, Kalman filter.

1. INTRODUCTION
Collaboration between human beings and robots takes advantage of their complementary features. On one hand, robots are able to do repetitive tasks which are dangerous or exhausting for people. On the other hand, humans can perform complex tasks which require intelligence. However, human-robot interaction in industrial workplaces may be dangerous for human operators because of the possibility of collisions with robots or with heavy objects. Therefore, a precise localization of human operators is needed. Nevertheless, most localization systems only register global position and orientation of the person. Motion capture systems don't have this drawback because they are able to measure full-body movements.

Motion Capture (MoCap) is a technique for digitally recording the movements of a person. The user of the system wears markers (or sensors) near each joint of his body and the motion capture system calculates his movements by comparing the positions and angles between the markers. Although the first motion capture systems were used in biomechanics [2] to study and model the movements of the human body, MoCap is applied in a wide variety of application fields nowadays: animation and computer graphics [5], robot teleoperation [6], human-robot interaction [7]…

The ability of motion capture systems to track precisely all the limbs of the human body not only guarantees the security of operators in industrial environments, but also provides significant information about their behaviour. This context-awareness provided by motion capture systems is the first requirement to be satisfied in order to apply 'Ambient Intelligence' (AmI) [1] in industrial environments where there is human-robot interaction. Context information can be interpreted in order to create 'intelligent environments' which adapt their operation to the user's needs. Thus, the robot workplace becomes context-aware and the robot controller is able to change the robot movements depending on the position of the human operator.

This paper analyses an inertial motion capture system which is used to track human operators who interact with a robotic manipulator in an industrial environment. Although the rotational measurements for each joint are very precise, the global translation position returned by this system accumulates high errors through time. Due to this fact, an additional UWB localization system, which provides more precise position measurements, has been used. In section 2 of this paper, different motion capture technologies are compared for their use in industrial workplaces and previous work on similar hybrid tracking systems is described. In section 3, both tracking systems are presented and evaluated. The Kalman Filter (KF) algorithm designed to combine the position data of both systems is explained in section 4. Section 5 describes some experimental results of this filter. Finally, the conclusions of this paper and future research are presented in section 6.

2. BACKGROUND

2.1 Motion Capture Technologies

Several motion capture technologies have been developed in the last decade [13]. However, not all of them are appropriate for industrial applications. Each one has different advantages and limitations depending on the physical principles on which it relies.

Mechanical MoCap systems (such as *Gypsy5* from *Animazoo*) are composed of a set of articulated rigid segments (exoskeleton) attached to the user's limbs and interconnected between them through electromechanical transducers (such as potentiometers). User motion is registered through voltage variations in the potentiometers. Although these systems have accurate measurements and low latencies, they are very uncomfortable for industrial workers who have to wear the exoskeleton for many hours a day.

Magnetic MoCap systems (such as *MotionStar* from *Ascension*) use a permanent transmitter (a set of three coils) that induces magnetic fields in the environment. These magnetic fields are measured by small receivers attached to the user's body and so user location is estimated. These systems are accurate and don't have light-of-sight restrictions. Nevertheless, they are not convenient for industrial workplaces because electronic devices and ferrous metals can change the electromagnetic fields induced by the transmitter and thus distort receiver measurements.

Optical MoCap systems (such as *Vicon MX* from *Vicon*) are based on the installation of a set of calibrated cameras which record images of the markers attached to the actor's body. The position of each marker is triangulated by using three or more images that contain the marker. Orientation is deduced from the relative orientation between three or more markers. These systems have high accuracy and high sampling rate, which enables quick movement registration. However, these systems are very complex to install in an industrial environment because they require many calibrated cameras in order to avoid marker occlusion (line-of-sight restrictions).

Inertial MoCap systems (such as *GypsyGyro-18* from *Animazoo*) use inertial sensors: accelerometers and gyroscopes. These sensors are tied to the actor's body. Actor's limb positions are calculated by double integrating the accelerations obtained from accelerometers and orientations are calculated by integrating the angular rates obtained from gyroscopes. These systems are the most appropriate for industrial environments because of their numerous advantages. Inertial sensors have low latencies, can be sampled at high rates, are self-contained and easy to install (no emitters are needed in the environment). Furthermore, they don't have line-of-sight restrictions as optical systems. However, the main disadvantage of these systems is the accumulation of errors through time (drift). This problem has been solved by developing hybrid systems which combine inertial measurements with other sensors.

2.2 Previous Work on Hybrid Tracking

Pose (position and orientation) estimation by inertial sensors is a well-studied field with applications in vehicle navigation, augmented reality (AR) and robotics. Most systems use additional sensors in order to correct drift accumulation of inertial sensors. Kalman filtering is the most frequently used technique for combining measurements of different sensors in this hybrid tracking systems.

Foxlin [4] develops a small device for head-tracking in virtual environments. It is composed by three orthogonal angular rate gyroscopes, a two-axis inclinometer and a two-axis compass. This system implements a complementary Kalman filter which estimates errors in orientation (from the inclinometer and the compass) and angular rate (from the gyros).

This device is an example of an inertial measurement unit (IMU): a package of inertial sensors (gyroscopes and accelerometers) which are used for tracking purposes by dead-reckoning estimation. Recent advances in sensor miniaturization have enabled the creation of small-sized compact MEMS (Micro-Electro-Mechanical Systems) IMUs, which are usually composed by gyroscopes, accelerometers and magnetometers. Accelerometers and magnetometers measurements are used to correct drift of orientation measurements from gyroscopes. *MTx* from *Xsens* and *InertiaCube3* from *Intersense* are two examples of commercial MEMS IMUs.

Recent inertial tracking systems use these commercial MEMS IMUs because they return precise orientation and don't have the typical drift problems of stand-alone gyros. However, these IMUs only obtain orientation measurements and no position information is supplied. An additional localization system is needed in order to obtain position measurements.

Caron et al. [3] propose a multisensor Kalman filter which combines GPS and IMU data to localize an autonomous land vehicle (ALV). This Kalman filter has two different measurements models (one for each sensor type) which are weighted according to fuzzy context variables that define sensors data reliability.

Ribo et al. [8, 9] present a wearable AR system that is mounted on a helmet. It consists of a real-time 3D visualization subsystem (composed by a stereo see-through HMD) and a real-time tracking subsystem (composed by a camera and an IMU). Sensor fusion is accomplished by an extended Kalman filter (EKF) which uses inertial measurements during the prediction step and vision-based measurements during the correction step.

Roetenberg et al. [10] have designed a wearable human motion tracking system consisting of a magnetic tracker (composed by a magnetic source and three magnetic sensors) and an inertial tracker (composed by three IMUs). The magnetic tracker is able to calculate relative distances and orientations between body segments while the inertial tracker registers accelerations and angular rates. A complementary Kalman filter is developed to correct inertial measurements with the magnetic ones.

Finally, Vlasic et al. [11] present a motion capture system which fuses accelerometers, gyroscopes and acoustic sensors by an EKF. The ultrasonic subsystem provides relative distances between sensors. However, this MoCap system and the previous one don't obtain absolute localization of users in the environment because they only return relative measurements. The MoCap system presented in this paper not only tracks all the limbs of the body but also gets the global position of the user in the environment.

3. SYSTEM ARCHITECTURE

The industrial environment built in this work project has three main devices (Figure 1): a *Mitsubishi PA-10* robotic arm, an *Animazoo GypsyGyro-18* MoCap system and an UWB localization system from *Ubisense.*

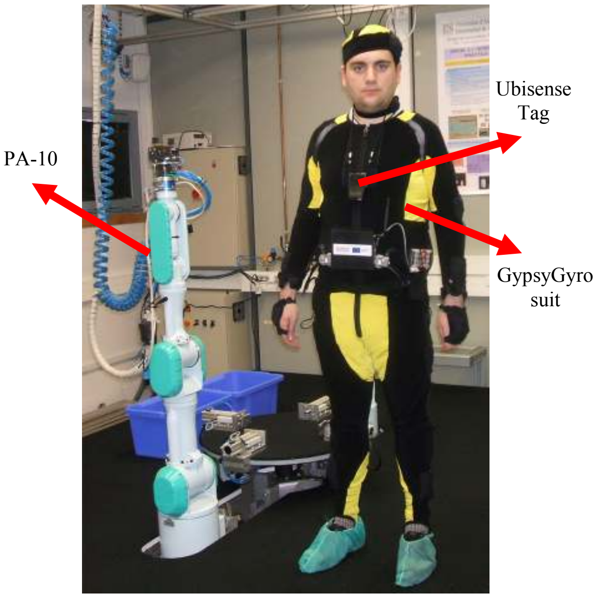

Figure 1. Main components of the industrial workplace: a PA-10 robotic arm (left) and a human operator (right), who wears a GypsyGyro-18 MoCap suit and an Ubisense tag.

The PA-10 is an industrial robotic arm (or manipulator) normally used for pick-and-place applications and component assembly. The robot controller is connected to a PC and can be controlled with a software library. The two tracking systems are described in the following sections.

3.1 Inertial Motion Capture System

The *GypsyGyro-18* is an inertial motion capture system composed of 18 small IMUs attached to a lycra suit which is worn by a human operator (Figure 1). Each IMU is an *InertiaCube3* from *Intersense* which measures the orientation (roll, pitch and yaw) of the operator's limb to which it is attached. This orientation data is transmitted through wireless link to a controller PC where global position of the operator is estimated with a footstep extrapolation algorithm.

All this movement data (limbs orientations and global body translation) is represented on a 3D hierarchical skeleton structure (Figure 2) whose size corresponds to the limbs' lengths. The hips node is the root node of the skeleton and represents global translation and rotation of the whole body in the environment. The other nodes of the skeleton represent limbs' rotations registered by IMUs. The rotation of each node is relative to the coordinate system of the parent node in the hierarchy of the skeleton.

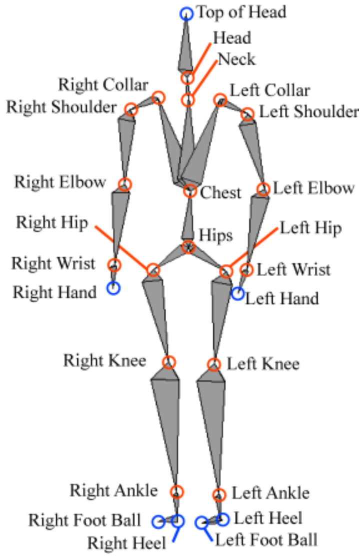

Figure 2. GypsyGyro-18 hierarchical skeleton.

The *GypsyGyro*-18 datasheet points out that orientation measurements calculated from each IMU have a resolution lower than 1º. Some experiments have verified these accuracy values, which are sufficient for general industrial manipulation tasks. Nevertheless, the accuracy of the global translation measurements estimated by the footstep algorithm is not specified. A set of experiments have been developed in order to quantify this accuracy. These experiments involve comparing the actual displacement of a person at different distances (200, 300 and 400 cm) with the displacement obtained from the MoCap system. Six trials have been executed for each distance and their results are shown in Table 1:

Table 1. GypsyGyro-18 translational error statistics (in cm).

Distance (cm)	Minimum error	Maximum error	Mean error	Standard Deviation
200	16.70	66.04	40.10	17.92
300	15.33	69.54	37.92	20.97
400	35.43	64.23	51.09	10.67

These errors are very high for industrial purposes. In some cases, they represent more than 30% of the actual distance. For this reason, an additional localization system (based on UWB technology) is needed in order to correct the translational errors of the *GypsyGyro-18.*

3.2 UWB Localization System

An Ultra-WideBand (UWB) radio positioning system from *Ubisense* is used to obtain more accurate translation information of the human operator.

The *Ubisense* system consists of two kinds of hardware devices: sensors and tags (Figure 3). Four sensors are situated at fixes positions on the localization area. Tags are small devices, of similar size to a credit card, which are carried by the users. A tag sends UWB pulses to the sensors, which use a combination of TDOA (Time-Difference of Arrival) and AOA (Angle of Arrival) techniques to estimate the global position (3D coordinates) of the user carrying the tag.

Sensors are connected to an Ethernet switch and send the location information to a controller PC which can access to this data through a software library. Slave sensors are also connected to a master sensor for synchronization in the TDOA algorithm.

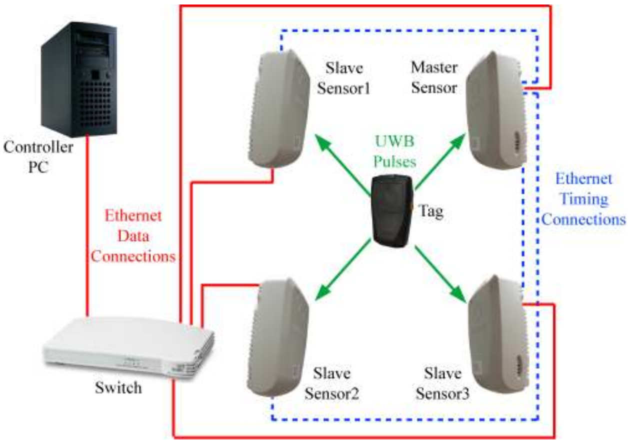

Figure 3. Ubisense architecture.

UWB is an appropriate technology for human positioning because of the following advantages:

- *Immunity to multipath fading:* UWB signals are much less susceptible to this effect than conventional RF (Radio-Frequency) technologies because UWB receivers are able to differentiate the original pulses from the reflected/refracted ones owning to their small time duration.

- *Immunity to RF interferences:* UWB signals have low power values which allow them to coexist with other RF signals despite their large bandwidth. Thereby, UWB systems have higher accuracy (15-30cm) than other RF technologies (1-3m).

- *Reduced infrastructure:* The number of sensors to be installed in the workplace is small. Other technologies (e.g. ultrasound) require denser sensor installations.

- *No line-of-sight restrictions:* In optical localization systems, there shouldn't be any obstacle (occlusion) between the emitter and the receiver. UWB technology doesn't have this limitation.

4. FUSION OF POSITION MEASURES

4.1 Algorithm Motivation

The first strategy for correcting the translational errors of the *GypsyGyro-18* would be to substitute its location data with the coordinates returned by the *Ubisense* system. However, this strategy is not suitable because the *Ubisense* has small data frequency (5-9fps) which will cause extremely high latencies for industrial environments. In addition, the *Ubisense* software applies a filter to the data which reduces the number of measurements, involving a variable data frequency. On the other hand, the *GypsyGyro-18* supplies constant data rates (30-120fps), but with accumulated errors in global translational measurements.

For these reasons, the best solution is to combine the global translational measurements from both systems. This fusion will correct the defects of one system with the advantages of the other system: The *GypsyGyro-18* will supply a high data frequency while the *Ubisense* will correct the accumulated errors with its location measurements. The *GypsyGyro-18* rotational measurements for each joint (obtained from IMUs) will remain unchanged because they are accurate relative rotation transformations in the skeleton (Figure 2).

4.2 Coordinate Transformation

The first step to combine the global position measurements of both tracking systems is to represent them in the same coordinate system (Figure 4). The *Ubisense* frame *U* is a fixed coordinate system in the workplace while the *GypsyGyro-18* frame *G* is determined every time the system is initialized. The *Ubisense* frame is selected as the reference frame and thus all measurements will be completely located in the environment.

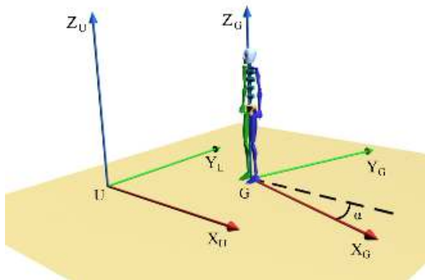

Figure 4. Ubisense and GypsyGyro-18 coordinate frames.

As shown in Figure 4, between the *GypsyGyro-18* frame and the *Ubisense* frame there is only a translation and a rotation about the *Z* axis by α. Therefore, the following equation will be used to transform a point $\mathbf{p}$ from the *GypsyGyro* coordinate system $\mathbf{p}^G$ to the *Ubisense* coordinate system $\mathbf{p}^U$:

$$\mathbf{p}^U = {}^U\mathbf{T}_G \cdot \mathbf{p}^G = \mathbf{Trans}\left(x_G^U, y_G^U, z_G^U\right) \cdot \mathbf{Rot}\left(\mathbf{z}^U, \alpha\right) \cdot \mathbf{p}^G \qquad (1)$$

Expanding the previous expression, the following equation will be obtained:

$$\begin{bmatrix} x^U \\ y^U \\ z^U \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) & 0 & x_G^U \\ \sin(\alpha) & \cos(\alpha) & 0 & y_G^U \\ 0 & 0 & 1 & z_G^U \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x^G \\ y^G \\ z^G \\ 1 \end{bmatrix} \qquad (2)$$

The angle α will be a known constant parameter (angle between the north direction and the *Y* axis of the *Ubisense* system). The only unknown variables of the transformation matrix ${}^U\mathbf{T}_G$ are the three coordinates of the translation vector from the *Ubisense* frame to the *GypsyGyro* frame. They can be calculated from equation 1 by substituting two corresponding measurements:

$$x_G^U = x^U - x^G \cos(\alpha) + y^G \sin(\alpha) \qquad (3)$$

$$y_G^U = y^U - x^G \sin(\alpha) - y^G \cos(\alpha) \qquad (4)$$

$$z_G^U = z^U - z^G \qquad (5)$$

After obtaining the transformation matrix ${}^U\mathbf{T}_G$, all the translational measurements from the *GypsyGyro-18* (3D position of the hips node) will be transformed from the *GypsyGyro-18* frame to the *Ubisense* frame by equation 1.

4.3 Kalman Filter Fusion Algorithm

Global translational measurements from both trackers are combined by a fusion algorithm based on a standard Kalman filter (Figure 5). First of all, the transformation matrix ${}^{U}\mathbf{T}_G$ will be initialized with equations 3-5 and the first two measurements. Thereby, the following measurements form the *GypsyGyro-18* will be transformed to the *Ubisense* coordinate system with equation 1.

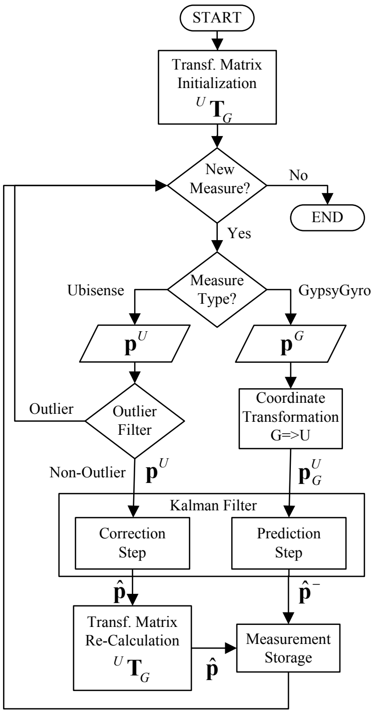

Figure 5. Fusion algorithm diagram.

After representing all measurements in the same coordinate system, a Kalman filter will be applied to them. The Kalman filter is a recursive stochastic technique which estimates the state $\mathbf{x} \in \Re^n$ of a dynamic system from a set of incomplete and noisy measurements [12]. The dynamic system is modeled by the following state-transition equation at time k (state model):

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{B}\mathbf{u}_{k-1} + \mathbf{w}_{k-1} \tag{6}$$

In equation 6, $\mathbf{A}$ is a $n \times n$ state-transition matrix, $\mathbf{B}$ is a $n \times p$ matrix, $\mathbf{u}$ is a $p \times 1$ vector with system inputs and $\mathbf{w}$ is a $n \times 1$ process noise vector (zero mean multivariate normal distribution with covariance matrix $\mathbf{Q}_k$).

In the current work, the state vector $\mathbf{x}$ is composed by the coordinates $\mathbf{p} = (x, y, z)$ of the global position of the user in the environment. $\mathbf{A}$ is a 3x3 identity matrix in order to incorporate directly the *GypsyGyro-18* measurements and $\mathbf{B}$ is a null matrix because there are no control inputs. The process noise covariance matrix $\mathbf{Q}$ is a diagonal matrix because state vector variables are not correlated. The diagonal terms of this matrix correspond to the mean error of the *GypsyGyro-18* measurements.

Sensor measurements $\mathbf{z} \in \Re^m$ at time k are modeled in a KF by the following equation (measurement model):

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \tag{7}$$

In equation 7, $\mathbf{H}$ is a $m \times n$ observation matrix which represents how the state of the system is registered by sensors and $\mathbf{v}$ is a $m \times 1$ measurement noise vector (zero mean multivariate normal distribution with covariance matrix $\mathbf{R}_k$). In this paper, $\mathbf{H}$ is a 3x3 identity matrix and $\mathbf{R}$ is a diagonal matrix whose diagonal terms correspond to the mean error of the *Ubisense* measurements.

The Kalman filter algorithm is composed of two steps: prediction step and correction step. The prediction step obtains a-priori estimate $\hat{\mathbf{p}}_k^-$ (equation 8) of the global position of the user and a priori estimate of the error covariance matrix $\mathbf{P}_k^-$ (equation 9) by incorporating position measurements $\mathbf{p}_k$ from the *GypsyGyro-18:*

$$\hat{\mathbf{p}}_k^- = \mathbf{A}\mathbf{p}_k + \mathbf{B}\mathbf{u}_{k-1} \tag{8}$$

$$\mathbf{P}_k^- = \mathbf{A}\mathbf{P}_{k-1}\mathbf{A}^T + \mathbf{Q} \tag{9}$$

On the other hand, the correction step uses *Ubisense* measurements $\mathbf{z}_k$ in order to eliminate error accumulation in previous a-priori estimates and thus compute an improved a-posteriori estimate of the global position $\hat{\mathbf{p}}_k$ (equation 11) and the error covariance $\mathbf{P}_k$ (equation 12):

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}^T \left(\mathbf{H}\mathbf{P}_k^- \mathbf{H}^T + \mathbf{R}\right)^{-1} \tag{10}$$

$$\hat{\mathbf{p}}_k = \hat{\mathbf{p}}_k^- + \mathbf{K}_k \left(\mathbf{z}_k - \mathbf{H}\hat{\mathbf{p}}_k^-\right) \tag{11}$$

$$\mathbf{P}_k = \left(\mathbf{I} - \mathbf{K}_k \mathbf{H}\right)\mathbf{P}_k^- \tag{12}$$

Finally, the transformation matrix ${}^{U}\mathbf{T}_G$ is re-calculated with the position estimate $\hat{\mathbf{p}}_k$. Thereby, the prediction step will be executed with the *GypsyGyro-18* rate and the correction step will be executed with the *Ubisense* rate.

Although the *Ubisense* system usually returns accurate positions, some measurements from the *Ubisense* system have big errors and shouldn't be incorporated to the Kalman filter. These outliers are eliminated by a filter which verifies that the distance between the current position and the previous one does not involve an excessive velocity for a person walking.

5. EXPERIMENTAL RESULTS

A set of experiments has been performed to verify the developed fusion algorithm. A human operator wearing the *GypsyGyro-18* suit and an *Ubisense* tag has walked along a preestablished linear path in the industrial workplace described in section 3. The measurements from both trackers are registered by a *Visual C++* program which is running in the controller PC where the *GypsyGyro-18* and *Ubisense* software libraries (DLLs) are installed. All these data are combined by the Kalman filter fusion algorithm which has been implemented in *Matlab* in order to obtain graphical representation of the resulting measurements.

Figure 6 shows the global translational measurements returned by the *GypsyGyro-18* and the *Ubisense* systems in a linear path in the

XY plane. They are represented in the *Ubisense* coordinate system. It is also represented the predefined linear path that the human operator has followed. The trajectory obtained from the *GypsyGyro-18* presents an error of 0.56m with regard to the preestablished path. This error is produced by the *GypsyGyro-18* footstep extrapolation algorithm because it sometimes estimates wrongly when the feet come into contact with the floor. This translational error justifies the need of the UWB system. However, the frequency of measurements from the *Ubisense* system (6Hz) is highly lower than the *GypsyGyro-18* data rate (30Hz), as it is shown in Figure 6. Because of this fact, the fusion of both systems is used in order to combine their complementary features.

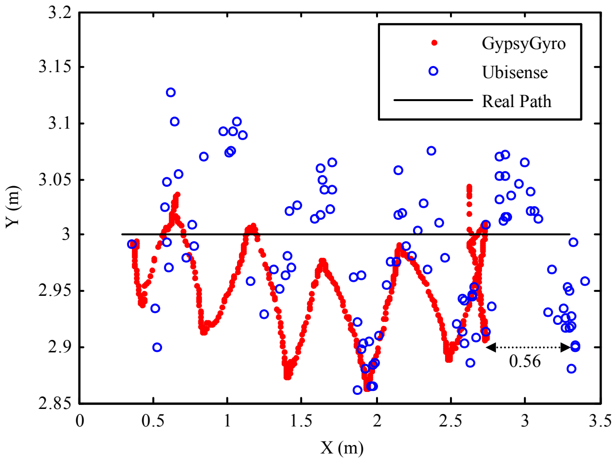

Figure 6. Comparison between the planned path and measurements from the GypsyGyro and the Ubisense systems.

Figure 7 shows the trajectory estimated by the Kalman filter fusion algorithm implemented in this paper. The *GypsyGyro-18* global translational error has been reduced to 0.14m and the resulting data rate is equal to the *GypsyGyro-18* frequency (30Hz).

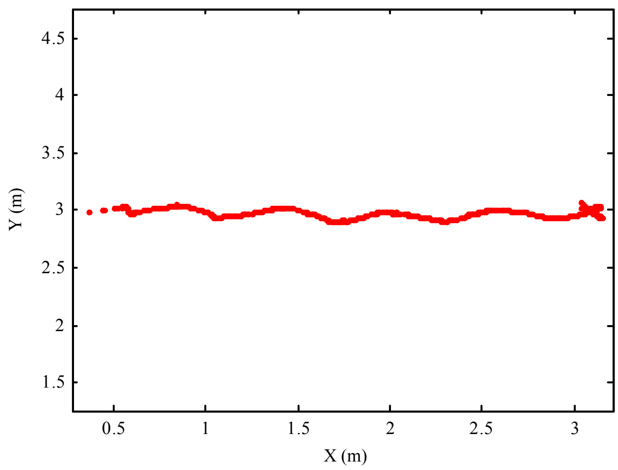

Figure 7. XY trajectory from the fusion algorithm.

Figure 8 represents the position estimates of the fusion algorithm that are obtained during the prediction step and the ones that are obtained during the correction step of the developed Kalman filter. *GypsyGyro-18* measurements are used in the prediction step in order to fill in the gaps between *Ubisense* measurements and thus obtain a more detailed trajectory. *Ubisense* measurements are used in the correction step in order to improve the accuracy of the global translation measurements from the *GypsyGyro-18*.

The current experiment has been performed several times and the obtained results have been very similar to the ones described above.

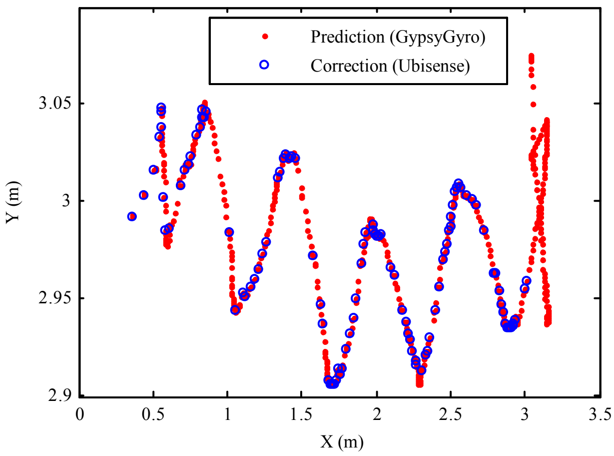

Figure 8. Prediction and correction estimates from the KF.

An additional experiment has been developed in order to verify the integration between the global translation data from the fusion algorithm and the limbs orientation measurements from the MoCap system. It is an interaction task between the *PA-10* manipulator and a human operator who is wearing the *GypsyGyro-18* suit and an *Ubisense* tag. The operator picks up an object which is out of the robot's workplace and gives it to the manipulator (Figure 9). Limbs orientations from the *GypsyGyro-18* and global displacement in the environment are shown over a skeleton in a 3D rendering software (Figure 9). The obtained animation shows that limbs movements are very accurate and the global localization of the human operator is appropriate.

6. CONCLUSIONS

In this paper, a hybrid tracking system for localizing precisely a human operator in a robotic workplace is developed. It consists of two components: an inertial motion capture system (*GypsyGyro-18*) and an UWB localization system (*Ubisense*). The MoCap system is able to register the movements of the operator's limbs with high precision. Nevertheless, the global position of the operator in the environment is not determined with sufficient accuracy. Thereby, an UWB localization system is used in order to obtain precise position measurements. A fusion algorithm based on a Kalman filter has been implemented in order to combine global position measurements of both systems. This fusion algorithm joins the advantages of the MoCap system (high data rate and accurate rotational data of each limb) and the UWB system (accurate global position estimation).

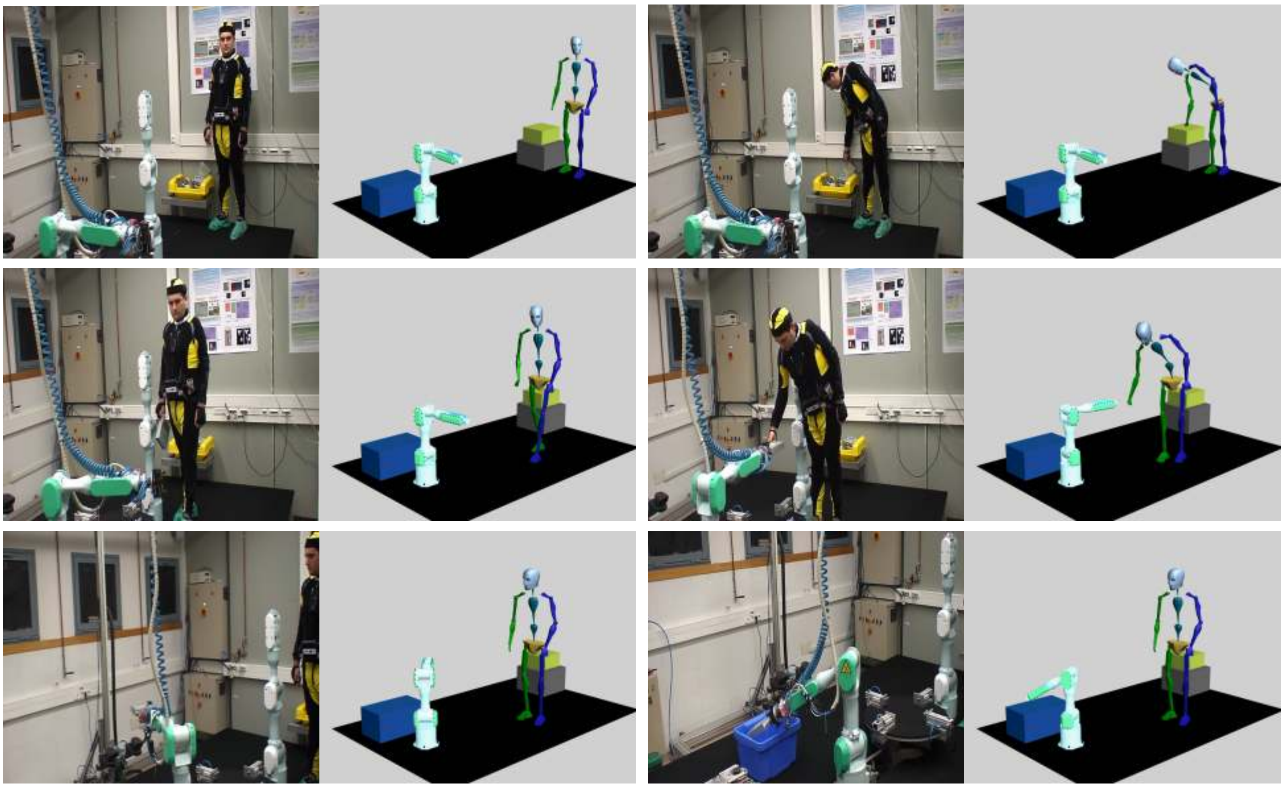

Figure 9. Frame sequence of a human-robot interaction task where a human operator gives an object to the robot.

The main advantage of this hybrid tracking system over previous systems (see section 2.2) is the combination of the global position of the operator in the environment with the precise location of all his limbs. Thereby, the operator is completely localized in the workplace. The precision of the system guarantees the security of the operator and allows the development of intelligent interactive tasks with robots.

In future work, more complex interaction tasks which take into account spatial relationships between the robot and the skeleton of the operator will be developed.

7. ACKNOWLEDGMENTS

This work is funded by the Spanish Ministry of Education and Science through the research project 'Design, Implementation and Experimentation of Intelligent Manipulation Scenarios for Automatic Assembly and Disassembly Applications' (DPI2005-06222) and the pre-doctoral grant AP2005-1458. The Valencian Government has also funded this research through the project 'infraestructura05/053'.

8. REFERENCES

[1] Alcañiz, M., and Rey, B. 2005. New Technologies For Ambient Intelligence. In Ambient Intelligence. IOS Press, Amsterdam, 3-15.

[2] Andriacchi, T.P., and Alexander, E.J. 2000. Studies of Human Locomotion: Past, Present and Future. Journal of Biomechanics, 33, 10, 1217-1224.

[3] Caron, F., Duflos, E., Pomorski, D., and Vanheeghe, P. 2006. GPS/IMU Data Fusion Using Multisensor Kalman Filtering: Introduction of Contextual Aspects. Information Fusion, 7, 2, 221-230.

[4] Foxlin, E. 1996. Inertial Head-Tracker Sensor Fusion by a Complementary Separate-Bias Kalman Filter. In Proceedings of the IEEE Virtual Reality Annual International Symposium, (Santa Clara, California, 1996). IEEE Computer Society, 185-194.

[5] Izani, M., Eshaq, A.R., Razak, A., and Norhan, N. 2004. A Study on Practical Approach of Using Motion Capture and Keyframe Animation Techniques. In Proceedings of the International Conference on Computer Graphics, Imaging and Visualization, (Malaysia, 2004). IEEE Computer Society, 52-55.

[6] Miller, N., Jenkins, O.C., Kallmann, M., and Mataric, M.J. 2004. Motion Capture from Inertial Sensing for Untethered Humanoid Teleoperation. In Proceedings of the 4th IEEE/RAS International Conference on Humanoid Robots, (Santa Monica, 2004). IEEE Robotics and Automation Society, 547-565.

[7] Onishi, M., Odashima, T., Luo, Z., and Hosoe, S. 2006. An Immersion-type 3D Dynamic Simulation Environment for Developing Human Interactive Robot Systems. Systems and Computers in Japan, 37, 10, 47-57.

[8] Ribo, M., Brandner, M., and Pinz, A. 2004. A Flexible Software Architecture for Hybrid Tracking. Journal of Robotic Systems, 21, 2, 53-62.

[9] Ribo, M., Lang, P., Ganster, H., Brandner, M., Stock, C., and Pinz, A. 2002. Hybrid Tracking for Outdoor Augmented Reality Applications. IEEE Computer Graphics and Applications, 22, 6, 54-63.

[10] Roetenberg, D., Slycke, P.J., and Veltink, P.H. 2007. Ambulatory Position and Orientation Tracking Fusing Magnetic and Inertial Sensing. IEEE Transactions on Biomedical Engineering, 54, 5, 883-890.

[11] Vlasic, D., Adelsberger, R., Vannucci, G., Barnwell, J., Gross, M., Matusik, W., and Popovic, J. 2007. Practical Motion Capture in Everyday Surroundings. ACM Transactions on Graphics, 26, 3.

[12] Welch, G., and Bishop, G. 2006. An Introduction to the Kalman Filter. Technical Report TR 95-041. University of North Carolina, Chapel Hill, North Carolina.

[13] Welch, G., and Foxlin, E. 2002. Motion Tracking: No Silver Bullet, but a respectable arsenal. IEEE Computer Graphics and Applications, 22, 6, 24-38.