Wearable Sensor System for Monitoring Body Kinematics

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Abstract — Existing human body motion capture solutions rely on camera based systems limited to confined measurements, or Inertial Measurement Units (IMUs) prone to noise and drift, resulting in position inaccuracies. This investigation demonstrates a proof-of-concept wearable sensor system which accurately monitors human body kinematics in real-time using Radio Frequency (RF) positioning sensors combined with MEMS based IMU sensors. In certain IMU orientations, we measured an average pitch error of < 2 degrees for the combined method, compared with 12 degrees for an IMU alone. This self-contained sensor network has applications including military training, gaming, sports and healthcare.

Index Terms — Body Area Network, Inertial Measurement Unit, RF Direction-of-Arrival, Sensor Fusion, Wearable sensors

I. Introduction

Several technologies have been developed for accurate real time position tracking of a human body. Typically these solutions have involved the use of IMUs, camera based systems or Radio Frequency (RF) positioning.

IMU sensors utilize accelerometers, gyroscopes and magnetometers to determine position and orientation. The multiple sensors are fixed relative to each other, and are thus able to provide readings from a single body. Post processing is required to combine the sensor signals into useable coordinates for localization. This results in a degree of uncertainty that increases over large movements or long time spans due to the susceptibility of IMUs to integration noise that creates position drift.

Camera based systems consist of cameras that visually track a certain feature or physical marker attached to an object. Typical body tracking systems require many markers to be externally attached to a user to get a clear reading. These markers can interfere with movement patterns and can be easily obstructed from the view of the camera. Furthermore, this type of system requires that the user be within the viewing range of the camera being utilized. A system of this type must be used in a confined, indoor environment that restricts the subject to within the range of the camera(s).

Radio frequency positioning typically uses the Time-of-Flight of various signals transmitted from radio transmitters. They operate on the principle that a signal takes a finite amount of time to travel between the transmitter and the receiver. Based on this time difference and the speed at which the signal travels, the relative distance can be determined between the transmitter and receiver. By using multiple signals at multiple frequencies, emitted from multiple transmitters, it is possible to triangulate the exact position of the receiver with respect to the transmitters. This is similar to Global Positioning System (GPS) geo-location techniques. The issue with this type of system is that radio signals travel at the speed of light which makes the measurement of the time of transmission and time of arrival difficult on smaller scales and requires precision synchronized system clocks at each node. Ultrawideband (UWB) systems, owing to the wide instantaneous RF bandwidths, can overcome some of these limitations at the expense of larger bandwidths [1] - [3].

Wearable technology human body tracking applications are described in [4] - [6]. Related work using RF Direction of Arrival is described in [7]. Given the limitations of the existing technologies, the system described in this paper was developed as an alternative solution.

II. System concept

We have developed a Proof-of-Concept (POC) hybrid wearable sensor network comprising IMUs and a 2.4 GHz RF positioning system. By incorporating two different positioning systems (IMU and RF), the sensors will be able to provide accurate positioning data over a range of movements. A position algorithm applies inverse kinematics and sensor fusion to determine the position. For situations where the RF signals are directly blocked by an object, or are otherwise obstructed, the IMU can be used solely for tracking. In the typical situation, where RF signals are visible, the positions reported from each sensor can be both used in a sensor fusion algorithm. This will help to further decrease noise and inaccuracies in the final reported position of each tag.

Small form factor tags with embedded RF transmitters and IMUs are attached to the subject's arms and legs and a receiver array worn on the subject's chest measures the tag RF Direction of Arrival (RFDOA) and receives the IMU data. See Figure 1.

Each tag is attached at various locations on the body and incorporates a Micro-Electro-Mechanical Systems (MEMS) IMU combined with a modulated RF transmitter that transmits a Continuous Wave (CW) RF signal containing the IMU data. This RF signal is used for calculating the RF Direction of Arrival (RFDOA) and RF phase information from each tag as received by the body worn receiver array.

Since it is a Continuous Wave (CW) waveform, synchronized system clocks at each tag are not required, thus simplifying the system compared to a pulse radar or time-of-flight RF system.

The Main Processor Unit (MPU) collects the tag data via the multi-element antenna array and forwards the data via a WiFi connection between the receiver array controller and the external remote computer that displays the data on a Graphical User Interface (GUI). The system block diagram is depicted in Figure 2.

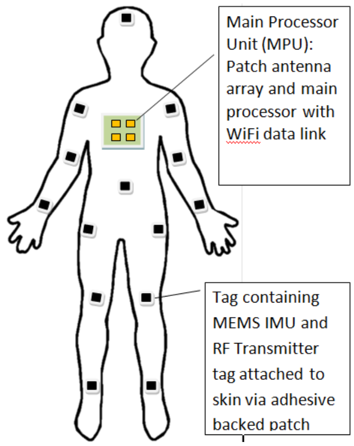

Fig.1. Wearable wireless sensor network comprising distributed tags that provide position information via an integrated IMU and RF transmitter contained in each tag. The MPU computes tag positions via RF Direction-of-Arrival (RFDOA) and range determination via the demodulated phase of the RF positioning signal to correct the IMU drift.

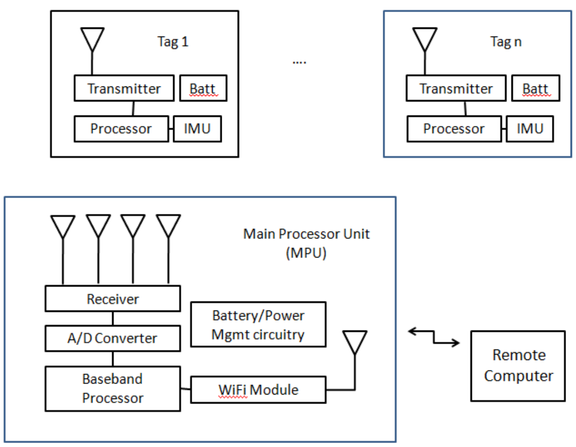

Fig. 2. System block diagram for the Wearable Sensor Network. Tags transmit Continuous Wave (CW) RF signal and Inertial Measurement Unit (IMU) data. Main Processor Unit (MPU) determines tag positions using phase demodulation of the received RF signal and IMU data and transmits the position data via WiFi to the display computer.

A. Antenna Array Design

We designed a switched array using Single-Pole-4-Throw (SP4T) RF switches for each 2x2 subarray and another SP4T switch to select one of the four sub-arrays.

We performed full wave electromagnetic (EM) simulations on the design to characterize the frequency response and pattern of the antenna. Figure 3 shows the top layer of the array design where patch elements and feed lines are visible. The bottom layer is an all conductor ground plane layer and is hidden for clarity.

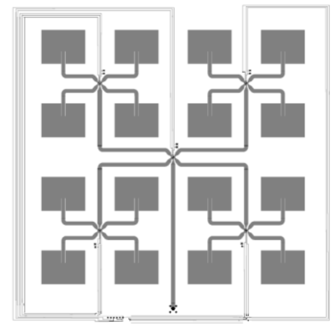

Fig. 3: Board layout of the 4x4 phased antenna array (9 inches x 9 inches). Larger traces are the RF feed lines and smaller traces are the switch control and power lines.

B. RF Direction of Arrival (RFDOA) Measurements

We validated the RFDOA position measurement capability by measuring the position of the tag antenna via the demodulated RF phase at the receiver and compared the received waveform with the position waveform as measured by a servo driven robotic arm that provided reference position readings. Figure 4 illustrates the array and tag intercept geometry in the vertical plane. The Root Mean Square (RMS) difference is 7.5mm and the mean difference is 0.2mm. The Standard Deviation (SD) of the difference is 0.7mm. For higher frequency changes in position, the RF signal has a sample rate that can accommodate enough bandwidth for up to several KHz of change in position.

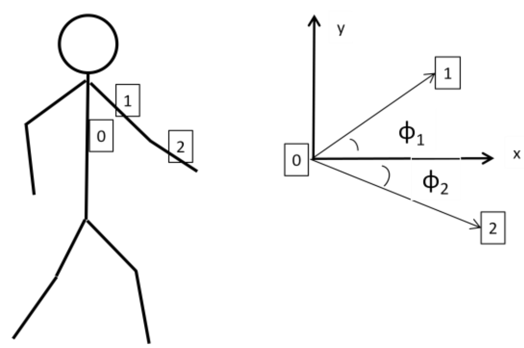

Fig. 4. Antenna array is located at position “0” with the array bore-sight along x axis. Tags are located at position 1 and 2.

C. RF Direction of Arrival (RFDOA) Estimation

Based on the antenna pattern information and using the Maximum Likelihood (ML) criteria, we were able to determine the RFDOA for each tag position using the simulated antenna pattern. The general ML problem can be formulated by first starting with a signal model. We can define the received signal model as:

$$r = S(\theta) + n(1) \quad (1)$$

where r is the antenna outputs, θ is the vector of RFDOA arrival angles and n is the noise matrix. S defines the sensor array’s behavior, in this case it is a function of individual antenna patterns and RFDOA. For a multivariate Gaussian probability density function with zero mean, the log likelihood function is defined as [8]:

$$L(\theta) = \left(\frac{k}{2}\right)\ln 2\pi - \left(\frac{k}{2}\right)\ \ln\ \det\left[\mathrm{K_n}\right] - 1/2\left\{\left[R - S(\theta)\right]^T K_n^{-1}\left[R - S(\theta)\right]\right\} \qquad (2)$$

where $\mathrm{K_n}$ is the noise covariance matrix and k is the number of sensors. For a maximum likelihood estimate (ML) the goal is to find θ_{ml} such that $L(\theta)$ is maximized by setting the derivative of (1) to zero. For the case where S is a linear function of θ, this derivative can be calculated fairly simply and there exists a closed form solution. For the case where S is non-linear we created a Maximum Likelihood estimator, $L(\theta)$, for all possible DOAs using the simulated antenna pattern. Figure 5 shows the ambiguity surface for the actual and estimated locations.

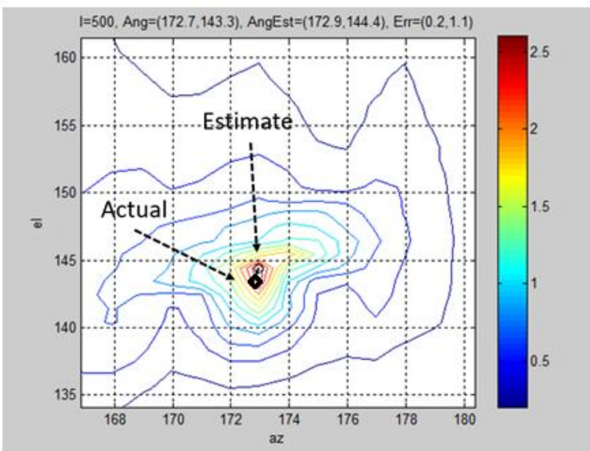

Fig. 5. Log likelihood contour surface for the ML estimation algorithm showing the actual (diamond) and estimated (circle) values. A sharper gradient of the ambiguity surface increases the estimation accuracy.

The RFDOA derived positions are shown in Figure 6. The scatter plot is created by plotting the reference robot arm position (red circles) from an initial calibration sweep of the robot arm. During this initial calibration sweep, the RF phase and amplitude response is measured to create a position estimate based on the Maximum Likelihood estimator. During a subsequent sweep representing the test measurement, the tag RF position estimates (blue circles) are determined from the Maximum Likelihood signal processing algorithm.

In the ideal case, the red and blue dots would overlay exactly if the ML estimator was perfect. A higher resolution search space for the ML estimator can mitigate these measurement errors by creating a search space with more entries thus reducing the nearest neighbor mapping distance when assigning a position estimate.

III. Conclusion

We demonstrated a proof-of-concept wearable sensor system using RFDOA and IMUs that achieved position measurement accuracies of less than 1 degree. In some cases, where the IMU error is significant, the RFDOA measurement is relied on and conversely, when there is RF blockage, the IMU position is used. The IMU yaw, pitch and roll (YPR) outputs are processed by an inverse kinematics algorithm that accounts for the tag position with respect to each limb joint to yield the spatial position of each tag. Measurement precision can be improved approximately 50% of the time over the YPR derived position by applying sensor fusion to combine the RFDOA output with the embedded IMU sensor in the tag of interest. The position accuracy of a few mm at 1 m range is similar to that of the Microsoft Kinect™ sensor.

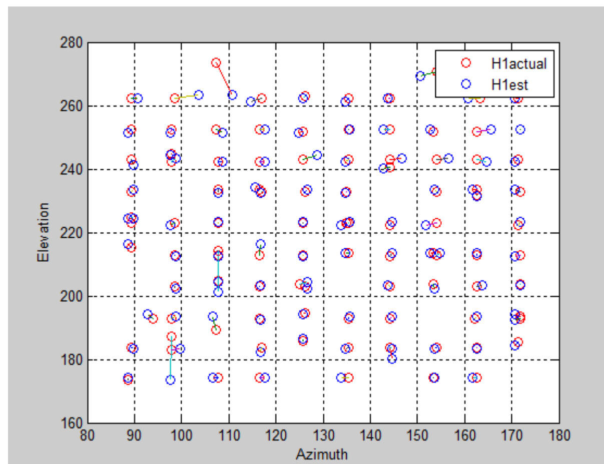

Fig. 6. RF position estimates (H1actual) versus reference (H1est) positions. The mean error is 0.1 degrees with a standard deviation of 1.3 degrees.

IV. Acknowledgements

The research reported in this document/presentation was performed in connection with contract/instrument W911QX-13-C-0148 with the U.S. Army Research Laboratory. The views and conclusions contained in this document/presentation are those of the authors and should not be interpreted as presenting the official policies or position, either expressed or implied, of the U.S. Army Research Laboratory or the U.S. Government unless so designated by other authorized documents. Citation of manufacturer's or trade names does not constitute an official endorsement or approval of the use thereof. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.

Preparation of this manuscript was supported in part by the National Science Foundation under grant number CBET 1160326.

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