UWB Positioning Using Six-port Technology and a Learning Machine

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Abstract—This paper presents a short-range positioning system based on six-port technology and the corresponding signal processing algorithms. Accurate positioning with high resolution of detected targets is achieved by utilizing both the impulse signal and the wideband phase discrimination characteristic of a six-port circuit operating in ultra-wideband (UWB) mode. This system has several advantages such as object penetration, multipath immunity and low probability of interception. Signal processing includes range estimation and position location algorithms. The range is estimated by analyzing the output signal pattern with support vector machines (SVM). Based on the estimated ranges between a target node and access points, the position of the target is determined using hyperbolic position location method. Ranging and position simulation results of the considered system are given for an indoor multipath channel. Accurate positioning has been achieved with an average root mean square error of 0.68 cm. The simulation results also show the robustness of the proposed system in a multipath channel.

I. INTRODUCTION

One of the recent and fascinating application areas for ultra-wideband (UWB) technology has been in the area of precision positioning [1]. In these applications, one takes advantage of the fact that short-pulse waveforms permit an accurate determination of the precise time of arrival (TOA). Short-pulse UWB techniques exhibit several distinct advantages such as high range measurement accuracy and resolution, low duty cycles, multipath immunity, increased operational security and ability to detect very slowly moving or stationary targets.

The multi(six)-port circuit was first used for microwave measurements [2]. It was also reported as a radar sensor [3][4] and a direct receiver using sinusoidal signals [5]. It was later introduced as a direct phase modulator for a single carrier signal [6]. The most important feature of a six-port circuit is the ability to perform accurate phase discrimination both in radio frequency (RF) and millimeter wave frequency range. Phase difference between two input signals is determined from four output signals of the circuit. Previous studies showed that six-port technology has advantages such as low cost, low power consumption, simplicity and extendibility. Research on design and fabrication technologies for six-port circuits such as monolithic microwave integrated circuit (MMIC) [7] and substrate integrated waveguide (SIW) [8] show the feasibility of fabricating wideband six-port circuits. The phase discrimination capability is feasible over a wide bandwidth as long as six-port circuits cover the same frequency range. For a UWB signal occupying an absolute bandwidth of more than 500 MHz, the implementation of wideband radio devices appears to be a particular challenge. As the above mentioned advantages, the six-port technology for impulse UWB applications seems promising but has not yet been studied thoroughly. A few six-port based UWB data communication applications have been recently reported [9][10]. This paper introduces a UWB positioning system based on multi(six)-port technology. Our purpose is to investigate the positioning application of six-port technology from a UWB perspective and present a hardware platform and learning machine algorithm for UWB ranging and positioning.

II. PROPOSED UWB POSITIONING SYSTEM WITH SIX-PORT

In an indoor positioning system (Fig.1), there are a limited set of access points (AP) or fixed reference nodes which are perfectly synchronized by sharing the same clock. These reference nodes are positioned at known coordinates \((X_k, Y_k)\) \(k = 1, 2, 3\) in the area to be monitored. Also in the mentioned area, there are certain number of target nodes whose positions \((X_i, Y_i)\) are to be determined.
II. HYPERBOLIC POSITIONING TECHNIQUE

The position of the target node can then be determined using the hyperbolic positioning technique. This technique assumes the different of arrival (TDOA), is used to determine the positions of target nodes can then be determined using the hyperbolic positioning technique. This technique assumes the different of arrival from different reference nodes removes the multipath effects. Thus, we adopt a machine learning approach to build a model of the relationship between six-port output signals and the corresponding target distances for training. After mapping original data to a high-dimensional space using a suitable kernel function, it is much easier to find an optimal linear regression function (2) through a training process in the high-dimensional space than in the original space.

\[
f(\vec{v}) = (w \cdot \vec{v}) + b
\]

The corresponding parameters \( w \) and \( b \) are given under the following conditions [11]:

\[
\begin{align*}
&\text{minimize } \frac{1}{2} ||w||^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \\
&\text{subject to } \begin{cases} \\
D_i - (w, \vec{v}_i) - b \leq \xi_i + \xi_i^* \\
(w, \vec{v}_i) + b - D_i \leq \xi_i + \xi_i^* \\
\xi_i, \xi_i^* \geq 0 
\end{cases}
\end{align*}
\]

where \( C \) is a capacity control parameter, \( \xi_i, \xi_i^* \) are slack variables coping with infeasible constraints on the output of the optimization problem, and \( \epsilon \) is a pre-specified constant which determines the acceptable deviation of estimations from actual outputs.

The linear solution is sought in the high-dimensional space and then projected back to the original space. The trained model is then used for distance estimation.

B. Positioning

With distances estimated from the above method, positions of target nodes can then be determined using the hyperbolic positioning technique. This technique assumes reference nodes share a common time reference and that the clock at target node is delayed by a time \( \delta \) with respect to the common time reference. The subtraction between times of arrival from different reference nodes removes the delay \( \delta \). The position of a target node in a bi-dimensional space is then determined as the intersection of hyperboloids in space, as described by the following equation [12]:

\[
\begin{pmatrix}
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \\
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \\
\vdots \\
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2}
\end{pmatrix} = \begin{pmatrix}
\hat{D}_1 - \hat{D}_1 \\
\hat{D}_2 - \hat{D}_2 \\
\vdots \\
\hat{D}_n - \hat{D}_{i,v}
\end{pmatrix}
\]

A. RANING AND Positioning Algorithms

For sinusoidal signals, an analytical expression of six-port phase discrimination function can be obtained [10]. For impulse UWB signals, it is not convenient to describe the function with an analytical equation. It becomes more difficult when we take into account multipath effects. Thus, we adopt a machine learning approach to build a model of the relationship between the six-port output signals and the target distance. SVM is chosen as the learning machine in this system because this novel learning algorithm has several advantages such as excellent generalization performance, theoretical properties and much less parameters to tune compared to artificial neural networks [11]. Another characteristic of SVM is that it suffers less from the curse of dimensionality by contrast to other learning methods, this is due to the use of kernel function which maps data from original space to high-dimensional (or even infinite-dimensional) feature space where the learning is carried out.

Consider the problem of fitting a set of training data:

\[
(\vec{v}_1, D_1), ..., (\vec{v}_l, D_l), \vec{v} \in X = R^n, D \in R
\]

where \( \vec{v}_1, ..., \vec{v}_l \) represent six-port outputs, \( D_1, ..., D_l \) are corresponding target distances for training. After mapping original data to a high-dimensional space using a suitable kernel function, it is much easier to find an optimal linear regression function (2) through a training process in the high-dimensional space than in the original space.

\[
\begin{pmatrix}
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \\
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2} \\
\vdots \\
\sqrt{(X_i - X)^2 + (Y_i - Y)^2} - \sqrt{(X_i - X)^2 + (Y_i - Y)^2}
\end{pmatrix} = \begin{pmatrix}
\hat{D}_1 - \hat{D}_1 \\
\hat{D}_2 - \hat{D}_2 \\
\vdots \\
\hat{D}_n - \hat{D}_{i,v}
\end{pmatrix}
\]
where \((X_i, Y_i)\) is the position of the target node, \((X_j, Y_j)\) are known positions of reference nodes, \(D_i\) represent the estimated distance between the \(k^{th}\) reference node and the target node \(i\), \(k \geq 3\) for a bi-dimensional space and for a \(k \geq 4\) tri-dimensional space. Equation (4) can be solved with various methods such as least square (LS) and iterative Taylor-series LS method [13].

IV. SIMULATION RESULTS IN MULTIPATH AND MULTIPATH-FREE CHANNELS

System simulation has been carried out with practical parameters. A pulse signal occupying a frequency band from 3.1GHz to 6.2GHz is used for simulation. Its fractional bandwidth is 0.67. The width of each pulse is 320 ps which is equivalent to a space resolution of 0.6 cm. The pulse repetition period is 20.48 ns.

An ideal six-port model has been implemented based on the structure of a typical six-port circuit [10]. As shown in Fig.2, its two input ports are fed with the reference pulse signal and receiving signals respectively. Samples from four output ports of the six-port circuit are fed to SVM algorithm model performing the range estimation.

A simulation over an additive white Gaussian noise (AWGN) channel is first performed. The simulation is further done over a simple three-ray model which includes a line of sight (LOS) ray and other two rays which have a distance difference of 19.6 cm between them. The selection of those two paths is based on the UWB channel model CM1 proposed by the IEEE 802.15.3a [14], which characterizes a line-of-sight (LOS) channel (0-4 m). The power decay factor is characterized with \(\gamma = 4.3\) as suggested in [13]. The pulse repetition period is greater than the root mean square (rms) delay spread \(\tau_{\text{rms}} = 5\text{ns}\) defined in the CM1 channel. Therefore, the reception of one pulse is not affected by late arrivals of replicas of previous pulses.

The channel is assumed to be stationary within an observation time, which is longer than pulse repetition period. The Doppler effect is ignored with an assumption of very slowly moving or stationary target nodes in indoor environments.

Fig.3 shows four received signals output from the six-port model in the considered three-ray channel compared with the reference signals. Based on those output signals, the SVM learning machine is trained and used to estimate distances between reference nodes and target nodes. The ranging estimation errors versus signal to noise ratio (SNR) simulated in an AWGN channel and three-ray channel are shown Fig.4. The results are compared with the lower limit in presence of AWGN given by the Cramer-Rao lower bound (CRLB) [12] which is a standard benchmark used to evaluate estimation methods. An average mean square error (MSE) of 1.4 has been achieved for ranging estimation by the proposed system in an AWGN channel typically at 10 dB SNR. The MSE value is equivalent to 0.71 cm which is calculated using the above mentioned practical parameters of the proposed system. A ranging MSE of 2.57, i.e. 0.96 cm, has been achieved in three-ray channel while keeping the same SNR level. The small MSE difference (0.25cm) between two types of channel reflects that the learning machine method is robust for multipath channel. The simulation results show the proposed system is close to the CRLB with a difference varying between 0.54 and 0.69 cm.

Based on the above accuracy ranging estimation, the positioning scenario considered for simulations is a bi-dimensional area with three access points (Fig.5). The first AP is located at (0, 0), the second AP at (1.5, 0.86) and the third at (0, 1.732). The estimated positions of target nodes are compared with their effective positions in Fig.5. To clearly show the difference between effective nodes and estimated nodes, positions of target 1 and its estimated positions are magnified in Fig.6 as an example. It shows a value of 0.68 cm for the average root MSE of the location estimation.

Fig.4. Range estimation errors in AWGN and multipath (three-ray) channels.

Fig.3. Six-port output signals in the multipath (three-ray) channel.
The effect of ranging estimation error on the accuracy of positioning can be reduced by adopting minimization procedures such as the least square error (LSE). Increasing the number of reference nodes is also helpful in reducing positioning errors [12].

V. CONCLUSION

In this paper, a novel six-port UWB positioning platform has been presented. Simulation models of a six-port circuit and the SVM learning machine for UWB positioning have been developed. Multipath effects have been incorporated in the performed simulations. The results show that the proposed system provides accurate position estimations and robustness in multipath channel. Using a learning machine for processing six-port output signals can provide the advantage of an adaptation to channel variation. In addition, the proposed platform can be implemented using a wideband six-port circuit with low-cost.

ACKNOWLEDGMENT

The authors would like to thank staff members and technicians from the POLY-GRAMES research centre for their fruitful discussions and co-operation.

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