

# 3D Accurate Location Stream Tracking and Recognition Using an Ultrasound Localization System

Lei Song\* and Yongcai Wang\*\*

\*NEC Labs, Beijing, China. Email: song\_lei@nec.cn

\*\*NEC Labs, Beijing, China. Email: wang\_yongcai@nec.cn

**Abstract**—High precision localization technology is the basis of fine-grained Location-based Service (LBS), such as interactive games, etc. A novel location system named *Dragon* is proposed, which provides target location in centimeter-level precision with 10Hz refreshing rate. *Dragon* uses a Fake-spot filtration algorithm to deal with the NLOS measurements and uses Extended Kalman Filtering (EKF) to handle the mistake of ranging detection and the ranging noises. Further, the high accuracy location stream obtained from *Dragon* is exploited for location-based control via recognizing the gesture of a moving target. Particularly, the design methodologies, establishment and performance evaluations of *Dragon* and the gesture recognition systems are presented.

## I. INTRODUCTION

High precision localization technology is an urgent need for fine-grained location-based services(LBS). Tracking and utilization of the accurate location streams generated by continuous movement of the targets are the key elements in such applications. Such kind of needs has lead to various designs and implementations of accurate indoor location systems. In general, different kinds of signals are used for accurate indoor localization[6], including infrared, radio frequency (RF), ultrasound (US), UWB and audible sound, etc. Comparing with other signals, we find that ultrasound is a promising means to be exploited for a practical indoor location system due to its high accuracy ranging, low cost, safety and user-imperceptibility.

So far, there are already some ultrasonic indoor location systems providing LBS. These typical examples include Bat[13] and Cricket [9], which use Time Of Arrival (TOA) ranging method of ultrasound to provide geometry based fine-grained localization. Recently, positioning accuracy, robustness, easy calibration and the cost of extra hardware are the main research considerations in ultrasound positioning systems. LOSNUS [10] applies the Time difference Of Arrival (TDOA) method to provide highly accurate ultrasound localization. In [4], the robustness of ultrasonic indoor positioning is improved by transmitter arrays. In [7], fast 3D ultrasonic localization is obtained by a light-weight multiple signal classification algorithm. In [11], a tag-free solution is studied which processes the echo signal captured by wall-mounted ultrasonic transducers to localize the untagged targets. In [8], a phase accordance method is proposed, which identifies the distance between an ultrasonic microphone and a moving transmitter by

rapidly estimating the frequency shift of the transmitted signal. In our previous work, we have developed an Autonomous Ultrasound Indoor Tracking System (AUITs)[1] which exploited the idea of Positioning on One Device (POD) to eliminate the calibration efforts than the systems using distributed reference points. We have also studied hybrid positioning system [2] to use ultrasound and RSS of WiFi for fine-grained, easily calibrated, large-scale indoor localization.

To pursue better location accuracy and higher location refreshing rates (number of location updates per second), we develop a novel indoor positioning system named *Dragon* based on [1] [2]. In previous TOA ranging based ultrasound location systems[13] [9][1], the non-line-of-sight (NLOS) distance measurements are the main cause of location error. In *Dragon*, the NLOS ranging measurements are treated specially by a Fake-spot outlier filtering algorithm. The algorithm calculates an estimated position using all the distance and then verifies the distances from this position to each receivers posteriorly. When the measured distance differs from the posterior verification distance than a threshold, it is judged as NLOS and removed as an outlier. The location calculation and outlier filtering loops repeat until all distance measurements are accepted as LOS distances. With this method, the location error is improved to around 10 centimeters, and the location refreshing rate is 10Hz per second. Tracking high accurate location streams makes *Dragon* suitable for more sophisticated LBS such as motion capture and gesture-based control. A 3D gesture recognition application is designed and implemented to demonstrate this ability, which recognizes the 3D gesture generated by a mobile target using online processing of the location streams by hypothesis testing.

The rest part of the paper is organized as follows. First, the system structure of *Dragon* is described, followed by the NLOS filtration algorithm in Section III. Then the gesture recognition method which utilizes the location streams is introduced in Section IV. Adequate experiments have been done to show the location precision of *Dragon* and the performances of proposed algorithms in Section V. Finally, the paper is concluded with discussion of future work.

## II. SYSTEM DESCRIPTION

In *Dragon* there are 3 kinds of components: tag, receiver and host. The system architecture is shown in Fig.1. Tag is

the mobile target whose location is unknown. Tag works in active mode which emits US + RF signals periodically or on demand.

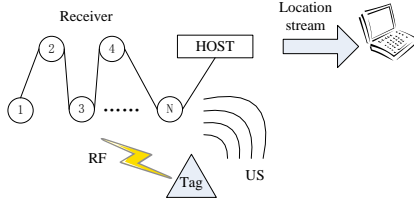


Fig. 1. Tag, receiver and host in Dragon

Receivers are installed in some fixed spots, whose coordinates are measured either manually or by self-calibration[1] when deployed. When a receiver hears the RF synchronization packet from the tag, a timer starts until the ultrasound signal arrives. The count value of timer is the propagation time of US. This propagation time is multiplied by the ultrasound speed with considerations of the temperature effects, facilitating ranging from the tag to the receiver.

After the distances between tag and each receivers are obtained, they are transferred to the host to calculate the tag's location. The host is more powerful than the receivers, which calculates the location of tag by EKF positioning algorithm[1]. However, due to the multi-path fading effects of US propagation, a receiver may measure a fault distance by detecting a NLOS US signal, which is a main cause of the location error. Fake-spot Filter algorithm is proposed to filter out the NLOS distance measurements during the position calculation. The outlier distances are filtered out iteratively using several loops of position calculation and consistency checking. Fig.2 shows this workflow. A distance is filtered out as an outlier when it differs obviously from the posteriori verification distance calculated by knowing the positioning result.

In position calculation, the overdetermined condition is needed in EKF (extended Karlman filter) for better positioning accuracy, where distance measurements from all receivers (generally larger than 3) are input to the loops of EKF and the Fake-spot Filter. In the worst case, EKF can track a target efficiently only if one reliable distance measurement is obtained by a receiver, so that the tags can be tracked continuously and robustly even in the case that some distance measurements are missed or most of them are filtered out.

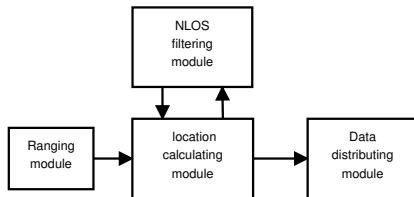


Fig. 2. Workflow of Dragon

### III. FAKE-SPOT FILTER ALGORITHM

For TOA ranging in indoor environment, detection of NLOS ultrasound is the common cause of ranging error. Such distance measurements are called outliers, which should be filtered out for positioning accuracy. In previous work, topologies information is used to conduct the filtering. The NLOS distance with large errors is filtered out if it breaks the triangle inequality constraints of the triangles formed by the tag-receiver, receiver-receiver distances [1]. However, topology based method can only filter out outliers with large enough errors[5] for the roughness of the triangle inequality constraints. The algorithm in [12] is topology-free, however [12] works only with small reflection.

In this paper, Fake-spot algorithm is proposed, which need neither statistical nor topology information, and works well under heavy reflection. The idea of this algorithm is to detect outliers by interactive position calculation and posteriori consistence checking to the distances. Initially, all distances are assumed to be inliers. A position is calculated based on these distances. This position is called Fake-spot. Then distances between Fake-spot and each receivers are calculated, which are called fake distance. Consistence checking is then carried out to compare the fake distance with the corresponding measured distance. If the maximum difference is less than a threshold, the set of distances is judged as valid and this iteration is over. Otherwise, the measured distance corresponding to this maximum difference is detected as outlier and removed, and the algorithm repeats as shown in Algorithm 1.

---

#### Algorithm 1 Fake-spot NLOS filtration algorithm

---

**Require:** Measured distances  $D_0 = \{d_1, d_2, \dots, d_N\}$  Receiver position  $X_0 = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_N\}$

**Ensure:** Valid distances  $D_v = \{d_{i_1}, d_{i_2}, \dots, d_{i_M}\}$

- 1:  $D_v = D_0$ , assume all distance are valid.
- 2: let  $F(D)$  be any locating algorithm.
- 3: **while**  $sizeof(D_v) > N_{min}$  **do**
- 4:    $\vec{x}_f = F(D_v)$  cal Fake-spot with  $F(D)$  from  $D_v$
- 5:   **for**  $(i = 1; i \leq sizeof(X_0); i++)$  **do**
- 6:      $D_f[i] = ||X_0[i] - \vec{x}_f||$
- 7:   **end for**
- 8:    $D_d = |D_f - D_v|$
- 9:    $maxDiff = Max(D_d)$
- 10:    $D_d[maxIndex] = maxDiff$
- 11:   **if**  $maxDiff \leq ThresholdDiff$  **then**
- 12:     **break**
- 13:   **else**  $\{maxDiff \geq ThresholdDiff\}$
- 14:     remove  $D_v[maxIndex]$  from  $D_v$ ;continue;
- 15:   **end if**
- 16: **end while**
- 17: **Output**  $D_v$ ;

---

Initially, all measured distances are reserved. In line 4 Fake-spot is calculated with any localization algorithm using measured distances. In this work, EKF is used. Line 3 to 16 filter out NLOS distance until there are not enough distances

in  $D_v$ .  $maxDiff$  stands for maximum difference between measured distances and fake distances. If  $maxDiff$  is small enough then all the distances are valid and the iteration stops; otherwise, it continues.

#### IV. GESTURE RECOGNITION

High accuracy location information is useful in human interface applications. Based on location stream, human gesture could be recognized. In such an approach, a Tag will work as a Magic Stick, whose position is continuously tracked by the Dragon with high frequency. Some spatial gestures of the Magic Stick are predefined, for example, “UP+Down”, “Down+UP”. Each predefined gesture can be matched to an action to control the computer.

Gesture Spotting and Gesture Recognition algorithms were proposed to process the 3D location stream of the Magic Stick to extract the gestures and to recognize the gestures. Gesture Spotting is to determine the start point and the end point of a gesture, i.e., to locate at a continuous location sequence which is possibly generated by a gesture of the Magic Stick. Gesture recognition is to process the location sequence to recognize the gesture.

Gesture Spotting and Gesture Recognition are carried out by detecting the pose change of the Magic Stick by using Hypothesis Testing method. In gesture spotting, a hypothesis  $H_1$  is mapped to the *pose change event* and another hypothesis  $H_0$  is mapped to the *pose unchange event*. Likelihood ratio is calculated to evaluate the occurrence probabilities of  $H_1$  and  $H_0$ . Particularly, the *start point* is detected when the occurrence probabilities  $R^t(H_1|H_0)$  is higher than a user-defined threshold  $\tau$ ; and the *end point* is detected when  $R^t(H_0|H_1)$  is higher than a user-defined threshold  $\gamma$ . For detecting the *start point* of a gesture

$$R^t(H_1|H_0) = \max \left( 0, R^{t-1}(H_1|H_0) + \log \frac{L(B_1|x_t)}{L(B_0|x_t)} \right) \quad (1)$$

where  $x_t$  is the newest location observation at time  $t$ ;  $L(B_1|x_t)$  and  $L(B_0|x_t)$  are the likelihoods of *pose change* and *pose unchange* events respectively when  $x_t$  is observed. The likelihoods are calculated by the deviations of location from the historical location observations [3]. When  $R^t(H_1|H_0) > \tau$ , a start point of gesture is detected. After a start point is detected, the end point of this gesture is detected when  $R^t(H_0|H_1) > \gamma$ .

In gesture recognition, a set of  $I$  hypotheses  $\{H_i\}$  is defined, and each hypothesis is mapped to a potential gesture component. We defined three basic gesture components ( $I = 3$ ): ‘U(UP)’, ‘D(Down)’, ‘H (Horizontal Movement)’. Each gesture sequence can be recognized as a sequence of ‘U’, ‘D’, ‘H’ gestures. When gesture components are recognized, high level gestures can be recognized by post processing the ‘U’, ‘D’, ‘H’ sequence. The algorithm to recognize the gesture components is given in Algorithm 2. In the algorithm,  $B_C$  is the current gesture in the gesture sequence, and  $w$  is the start point of the current gesture.

#### Algorithm 2 Online gesture component recognition algorithm

---

```

1:  $w=1$ , initialize the last gesture change point  $w$ .
2: for ( $n=1$ ;  $n \leq N$ ;  $n++$ ) do
3:   for ( $i=1$ ;  $i \leq I$ ;  $i++$ ) do
4:      $T_i^n = \max \left( 0, T_i^{n-1} + \log \frac{\Pr(x_n|B_i)}{\Pr(x_n|B_C)} \right)$ 
5:   end for
6:    $T_{i^*}^n = \max_{1 \leq i \leq I} \{T_i^n\}$ ;
7:   if ( $T_{i^*}^n > \tau$ ) then
8:      $\lambda^* = \max_{w < \lambda \leq n} \{\lambda | T_{i^*}^\lambda = 0, w < \lambda < n\}$ ;
9:      $w = \lambda^*$ ;
10:     $B_C = B_{i^*}$ ;
11:    Output  $B_C$ ;
12:    Output  $w$ ;
13:   end if
14: end for

```

---

In Line 4, the occurrence probabilities of all hypotheses are calculated. In Line 6, the most possible hypothesis  $H_{i^*}$  is found among all hypotheses. If its occurrence probability is larger than a threshold,  $B_{i^*}$  is accepted as the current gesture, and the starting point of this new gesture is calculated by Line 8.

#### V. PERFORMANCE EVALUATION

In order to evaluate NLOS filtration effect and location accuracy in Dragon, an indoor locating environment is established. Fifteen receivers are arranged in the roof of a room while the dimension of the room is  $600cm \times 400cm \times 260cm$ . During experiment, 100 spots are chosen as test points. The positions of these points and 15 receivers are measured with DEM(Electronic Distance Measuring Device) as ground truth.

Fake-spot algorithm is verified by contrasting real distances with the measured distances before and after the filtering. Mean measured distances and related real distances before filtering are shown in Fig.3(a). After filtration, the comparison of the remained measured distances and the real distances is shown in Fig.3(b). This contrast shows that after the filtration, NLOS distances which are 10cm greater of more than the corresponding real distances are filtered out.

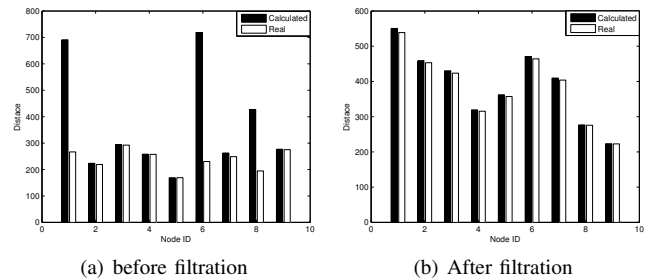


Fig. 3. Ranging error contrast

The location accuracy performance is shown in Fig.4. The circle stands for the real position while the square stands for the location result. From this figure we can find the location

accuracy higher in the center of the room than in corners. The related CDF(Cumulative distribution function) is shown in Fig.6. The reason is that in center of the room the number of valid distances is higher than that near corners, as shown in Fig.5. The size of the spot indicates the number of valid distances received at the corresponding position after the Fake-spot algorithm.

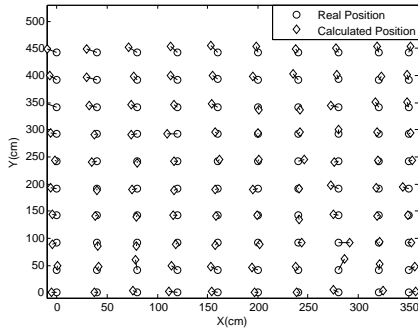


Fig. 4. indoor localization error

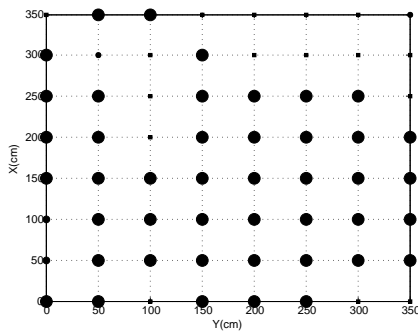


Fig. 5. number of valid distances

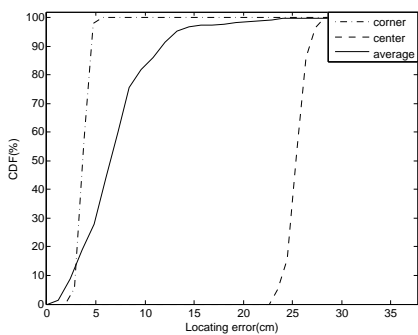


Fig. 6. Mean location error

The gesture recognition performance has also been tested, where previously defined 3D gesture components “Up(U)”, “Down(D)” and “Horizontal movement(H)” are recognized from the location stream. A tag is moved manually by a user and the ground truth is recorded. For an experiment to recognize 200 gestures, the correct rate is shown to be higher than 90% for the tag moving at normal hand-moving speed.

## VI. CONCLUSION

In this paper, an ultrasound-based location system, Dragon has been proposed to provide high precision location data stream. A Fake-spot filter algorithm has been involved which filters out the NLOS distances without limiting the topology of the receivers. EKF localization algorithm has been implemented in Dragon for robust and accurate tracking of single and multiple tags. As the result, dragon produces location stream in centimeter-level accuracy with 10 Hz location rates. Based on the highly accurate location stream, location-based gesture recognition has been proposed with the hypothesis testing method. The correct recognition rate has been shown to be higher than 90% for normal tag moving speed. Designing more sophisticated distance filter algorithm, improving the location refreshing rate, and building location gesture control system will be the future research directions.

## REFERENCES

- [1] Autonomous ultrasonic indoor tracking system. In *ISPA '08*, pages 532–539, 2008.
- [2] HIPS: a calibration-less hybrid indoor positioning system using heterogeneous sensors. In *PerCom 2009. IEEE International Conference on*, pages 1–6, 2009.
- [3] Pospush: A highly accurate location-based information delivery system. *UBICOMM '09*, pages 52–58, 2009.
- [4] S. Holm and C. Nilsen. Robust ultrasonic indoor positioning using transmitter arrays. In *IPIN 2010*, pages 1–5, sept. 2010.
- [5] L. Jian, Z. Yang, and Y. Liu. Beyond triangle inequality: Sifting noisy and outlier distance measurements for localization. pages 1–9, Mar. 2010.
- [6] H. Liu, H. Darabi, P. Banerjee, and J. Liu. Survey of wireless indoor positioning techniques and systems. *Systems, Man, and Cybernetics, IEEE Transactions on*, 37(6):1067–1080, nov. 2007.
- [7] K. Mizutani, T. Ito, M. Sugimoto, and H. Hashizume. Fast and accurate ultrasonic 3d localization using the tsat-music algorithm. In *IPIN 2010*, pages 1–5, 2010.
- [8] S. Nakamura, T. Sato, M. Sugimoto, and H. Hashizume. An accurate technique for simultaneous measurement of 3d position and velocity of a moving object using a single ultrasonic receiver unit. In *IPIN 2010*, pages 1–7, sept. 2010.
- [9] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan. The cricket location-support system. *MobiCom '00*, pages 32–43, 2000.
- [10] H. Schweinzer and M. Syafrudin. Losnus: An ultrasonic system enabling high accuracy and secure tdoa locating of numerous devices. In *IPIN 2010*, pages 1–8, 2010.
- [11] E. Wan and A. Paul. A tag-free solution to unobtrusive indoor tracking using wall-mounted ultrasonic transducers. In *IPIN 2010*, pages 1–10, sept. 2010.
- [12] X. Wang, Z. Wang, and B. O’Dea. A toa-based location algorithm reducing the errors due to non-line-of-sight (NLOS) propagation. *Vehicular Technology, IEEE Transactions on*, 52(1):112–116, 2003.
- [13] A. Ward, A. Jones, and A. Hopper. A new location technique for the active office. *Personal Communications, IEEE*, 4(5):42–47, oct 1997.