Space Encoding Based Compressive Tracking with Wireless Fiber-Optic Sensors

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Abstract. This paper presents a distributed, compressive multiple target localization and tracking system based on wireless fiber-optic sensors. This research aims to develop a novel, efficient, low data-throughput multiple target tracking platform. The platform is developed based on three main technologies: (1) multiplex sensing, (2) space encoding and (3) compressive localization. Multiplex sensing is adopted to enhance sensing efficiency. Space encoding can convert the location information of multi-target into a set of codes. Compressive localization further reduces the number of sensors and data-throughput. In this work, a graphical model is employed to model the variables and parameters of this tracking system, and tracking is implemented through an Expectation-Maximization (EM) procedure. The results demonstrated that the proposed system is efficient in multi-target tracking.

Keywords: Human tracking · Multiplex sensing
Compressive sensing · Space encoding

1 Introduction

Indoor environments monitoring has been demanded in many areas. The applications include human counting, tracking, identification, activity recognition, and situation perception, etc. The purposes are to provide secure and intelligent working and living spaces to users through the surveillance of the environments. Among these applications, human tracking is a very challenging but interesting application, and is receiving more and more attentions. Traditional human tracking systems in indoor environments are based on video cameras. Such systems have been widely applied due to its visual characteristic [1]. Nowadays, some wireless sensor based human tracking systems have been developed and demonstrated with a satisfied performance especially under severe conditions such as poor illumination, low computation, disguise, and so on.

The wireless sensor based human tracking systems are advantageous in (1) large surveillance area; (2) low data throughput; (3) robustness; (4) multiple

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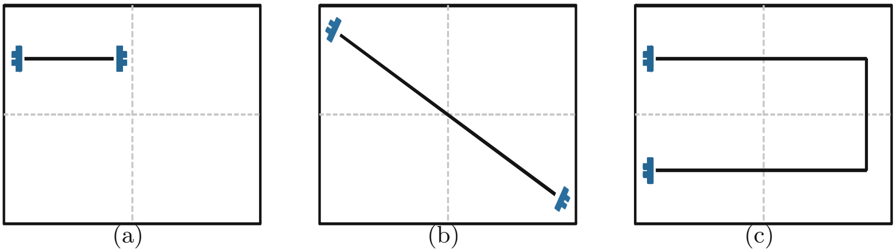


Fig. 1. (a) Simplex fiber-optic sensing; (b) duplex fiber-optic sensing; (c) multiplex fiber-optic sensing.

sensing modalities. Radar, sonar, acoustic sensor based tracking systems are proposed in [3,4]. Radar-based systems demand a large amount of power supply, therefore, they are usually applied in military fields [2]; while acoustic sensor based systems are prone to be interfered by noise, and their performance is limited in silent environments. The pyroelectric infrared (PIR) sensor is able to detect the infrared irradiation of human motions, it is appropriate to be used in human tracking. A typical work is proposed in [5], which uses wireless distributed pyroelectric sensors to achieve multi-human tracking and identification.

Whatever sensor is used to form a human tracking system, the goals are to implement low-data-throughput and energy-efficient sensing. Recently compressive sensing technology has been proposed and applied in image processing and information retrieval [6,7]. It has been proved that compressive sensing can further reduce the data samples but still guarantee the successful reconstructions. Inspired by this technique, we propose a wireless sensor based human tracking platform using compressive sensing. Furthermore, we extend compressive sensing concept from data processing to sensing mode and sampling geometry, namely, we start compress measurements in sensing and sampling phases.

Other than the typical wireless sensor based human tracking systems, mainly the PIR sensor based systems, in this paper, we propose to use a new sensing modality, fiber-optic sensors to implement human tracking. Compared with PIR sensors, fiber-optic sensors are more suitable to human tracking. By adopting multiplex sensing, space encoding and compressive localization, the sensing efficiency and data compression are enhanced. The multi-target tracking is achieved through a graphical model and expectation-maximization (EM) approach.

2 System Model

2.1 Multiplex Fiber-Optic Sensing

As we know, sensing is the process that converting physical information into signals that can be read and observed by an instrument. The fiber-optic sensors can be used to convert the presence and pressure information of targets into light intensities to enable localization and tracking. Multiplex sensing technique is inspired by the antenna of insects which is able to increase the utilization ratio of single sensor cells. Here, in our system, we employ multiplex sensing to enable each fiber-optic sensor to detect multiple regions rather than just one region. In this way, all the sensors can be fully utilized and the number of sensors needed can be reduced dramatically. Such a method can improve the sensing efficiency but at a price of increasing ambiguities in localization. The fiber-optic sensing formats are shown in Fig. Compared with simplex sensing (Fig. 1(a)), multiplex sensing (Fig. 1(b), (c)) consumes less sensors to cover the same size regions.

2.2 Space Encoding Schemes

Space encoding is to segment the monitored area into different blocks and use a certain sensors to encode each block. Thus, when a target appears in a certain block, the corresponding code indicates the target's location. The purpose of using space encoding technology is to enhance the feasibility and efficiency of monitoring. Fiber-optic sensors are appropriate for space encoding due to its flexibility and detection modality. There are multiple space encoding schemes suitable for fiber-optic sensors. The ideal encoding scheme is named decimal encoding, in which a single block is encoded by only one sensor. Apparently, this encoding scheme is able to get a high accuracy with a minimum of ambiguity. The number of sensors, however, could be very large for a wide area. In comparison, binary encoding scheme can reduce the sensor consumption dramatically. For example, encoding a 4 blocks area, decimal encoding scheme needs 4 sensors, while binary encoding scheme only needs 2 sensors, as shown in Fig. 2.

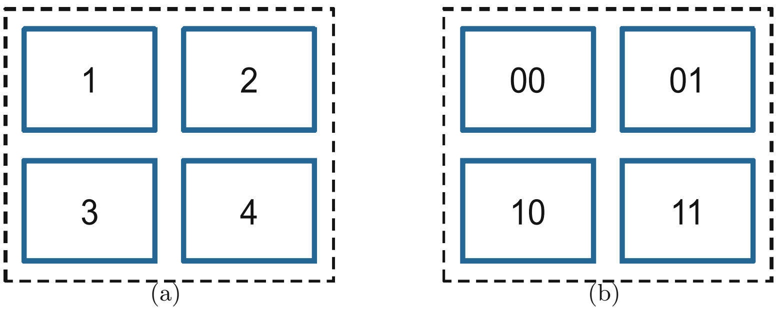
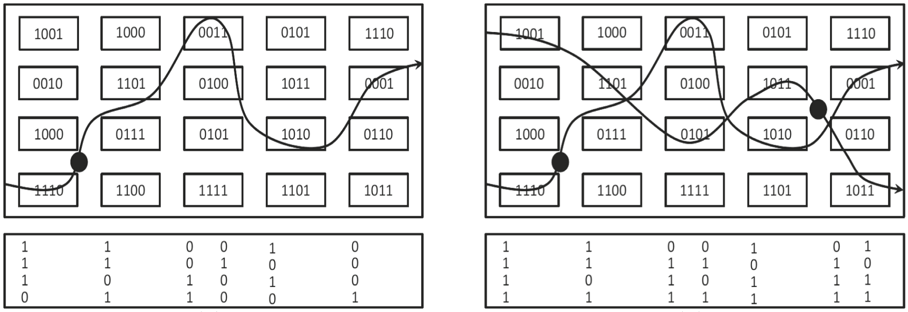


Fig. 2. Space encoding for a 4-blocks region. (a) Decimal encoding scheme; (b) binary encoding scheme.

2.3 Distributed Binary Space Encoding

Suppose n fiber-optic sensors are available in the system, and they are used to monitor a space which is divided into m blocks $\boldsymbol{\gamma} = \{\gamma_1, \gamma_2, \cdots, \gamma_m\}$. Each block



(a) (b)

Fig. 3. Illustrations of space encoding for (a) one target case; (b) two targets case.

γ_i is encoded by n fiber-optic sensors, and the corresponding code will be a n-bit binary string, represented by $C_i = \{c_{i1}, \cdots, c_{in}\}$, as shown in Fig. 3. c_{ij} is generated when a target presents in j_{th} block, so

$$c_{ij} = I(\Omega_i \cap \varphi(\gamma_j)) \tag{1}$$

where $I(\cdot)$ is a logic function whose output is "0" or "1"; Ω is the sampling geometry of sensor i; $\varphi(r)$ is the target at location r; and $\cap$ represents bit-wise AND operation. Therefore, with n fiber-optic sensors deployment, the observation area is encoded into a set of n-bit codes.

When only one target presents within the observation area, the measurement y, which is a $n \times 1$ vector, is given by

$$y = Cx_1 \tag{2}$$

where $C = [c_{ij}]^T$, which is a $n \times m$ matrix, and $x_1 = I(\boldsymbol{r} \in \boldsymbol{\gamma})$, which is a $m \times 1$ binary vector with only one '1' element.

When K targets present within the observation area, the measurement $n \times 1$ vector, y becomes

$$y = \bigcup_{k=1}^{K} Cx_k = C \odot x \tag{3}$$

where $\cup$ denotes the bit-wise OR operation, x_k is the measurement vector for the k_{th} target, $\odot$ denotes the saturation multiplication, *i.e.*, $A \odot x = I(Ax \geq 1)$ if the upper bond is 1 and I is a matrix with only '1's. The example of the binary measurement sequence for one and two targets cases are shown in Fig. 3.

2.4 Compressive Localization

The complexity of the compressive localization for multiple targets comes from the bit-wise OR operation in Eq. 3. To localize K targets with small errors, it requires a high degree of independence among the codes. However, an increase of the independence will lead to an increase of sensors.

Given the space codes matrix H, the binary compressive localization problem is solved by [8]

$$\hat{x} = \underset{x}{\operatorname{argmin}} \|x\|_1 \ s.t. \, y = H \odot x \tag{4}$$

where y is the binary measurement. For simplicity purpose, the nonlinear constraint, $y = H \odot x$, can be replaced by a linear constraint, $y = HX$ by rounding the real number valued solution to a binary vector. Alternatively, the constraint can be further replaced by the binary compressive sensing constraint, $y = H \oplus x$. The original problem is finalized as

$$\hat{x} = \underset{x}{\operatorname{argmin}} \|x\|_1 \ s.t. \, y = [H2I][x; z] \tag{5}$$

where I is the identity matrix and $z > 0$ is an auxiliary vector.

The selection of two solutions is determined by the number of targets and the code matrix.

3 Graphical Model Based Space Decoding and Multi-target Tracking

3.1 Graphical Model

Multiple target tracking is a challenging issue due to the involvement of a bunch of unknown variables and complex conditions. With different characteristics of these variables in multi-target tracking systems, the system models under various conditions can be summarized to:

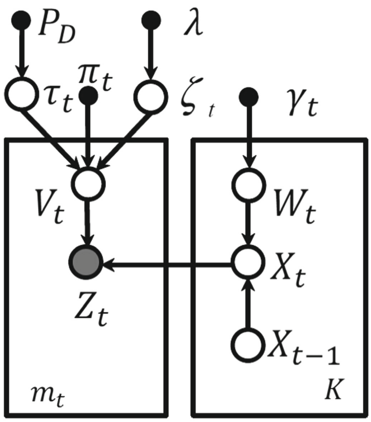


Fig. 4. Multi-target tracking model with unknown number of false alarms.

Case 1 - known data-to-target association
Case 2 - unknown data-to-target association
Case 3 - unknown tracker-to-tracker association
Case 4 - unknown detection failures
Case 5 - unknown false alarms
Case 6 - varying number of targets.

Let $X_t = (x_t^1, x_t^2, \cdots, x_t^k)$ denote the states of k trackers, X_{t-1}^k is the previous state of the k_{th} tracker. $Z_t = (z_t^1, z_t^2, \cdots, z_t^m)$ denotes m observations at time t, which are related and dependent upon X_t. The hidden variables are given as follows:

V_t data-to-tracker association matrix
W_t tracker-to-tracker association matrix
κ_t number of targets
τ_t number of detectable targets
ζ_t number of false alarms.

The first case is the simplex tracking model, in which correct data-to-tracker association can be achieved. Specifically, the k_{th} tracker X_t^k is associated with measurement Z_t^k correctly, and the current states of trackers can be associated with previous states of the same trackers correctly. As for such cases, the multiple targets can be tracked with a high accuracy. While for other cases, if the data-to-tracker association, tracker-to-tracker association, or detection failure is unknown, then the tracking model becomes more complicated and correspondingly the tracking error will be larger. In this work, we establish a more complicated tracking model to investigate the case that the false alarms are unknown.

The system model is shown in Fig. 4. For the cases of unknown false alarms, the number of false alarms is denoted as ζ_t, which is a Poisson random variable with an average value of λ. The location of false alarms yields a uniform distribution with a density value of $\frac{1}{O}$, where O is the volume of the observation space. All the false alarms belong to a clutter tracker X^0; hence, the dimension of the association matrix V becomes $m_t \times (K+1)$. Assuming the measurements are reordered such that

$$z_j | \in [m_t - \zeta(V_t) + 1, m_t] \tag{6}$$

where z_j is a false alarm, then the clutter tracker model is given by

$$p(Z_t | X_t^0, V_t) = \prod_{j=m_t-\zeta(V_t)+1}^{m_t} (\frac{1}{O})^{V_{j0}} \tag{7}$$

Given that $p(\zeta|\lambda)\frac{\lambda^\zeta e^{-\lambda}}{\zeta!}$, $p(\zeta_t)$ could be represented by

$$p(\zeta_t) = \prod_{m=1}^{m_t} [p(\zeta_t|\lambda)]^{\delta(\zeta_t - m)} \tag{8}$$

then

$$p(V_t|\tau_t, \zeta_t) = \prod_{j=1}^{m_t-\zeta_t} \prod_{k=1}^{K} (\pi_t^k)^{V_t^{jk}} \tag{9}$$

and

$$p(Z_t|X_t, V_t) = \prod_{j=1}^{m_t-\zeta(V_t)} \prod_{k=1}^{K} p(z_t^j|x_t^k)^{V_t^{jk}} p(Z_t|X_t^0, V_t) \tag{10}$$

where $K - \tau_t$ columns of the association matrix, V, are all-zero vectors.

The joint probability density function of X, Z, V, W, τ, ζ is given by

$$\begin{aligned} p(X_{1:t}, Z_{1:t}, V_{1:t}, W_{1:t}, \tau_{1:t}, \zeta_{1:t}) &\equiv p_{1:t}^{X,Z,V,W,\tau,\zeta} \\ &= p_{1:t-1}^{X,Z,V,W,\tau,\zeta} p(Z_t|X_t, V_t) p(X_t|X_{t-1}, W_t) p(W_t) \\ &\quad p(V_t||\tau_t, \zeta_t) p(\tau_t) p(\zeta_t) \end{aligned} \tag{11}$$

3.2 Multiple Target Tracking

The challenge of multi-target tracking is that some hidden variables exist in the sequential estimation and prediction process such as the number of detected targets, the number of trackers, the number of false alarms, and data-to-target association. Let $\mathcal{H}$ represent all the hidden variables, then the general solution can be obtained by using Expectation-Maximization (EM) optimization.

1. **E-step:** estimate the distribution of hidden variables from the predicted target state, $\hat{x}_t$, and measurements, z, by conditioning the joint distribution, $p(\mathcal{H}, x, z)$, which is represented by

$$p(\mathcal{H}|\hat{x}, z) = \frac{p(\mathcal{H}), \hat{x}, z}{\Sigma_{\mathcal{H}} p(z|\hat{x}, \mathcal{H}) p(\hat{x}|z, \mathcal{H}) p(\mathcal{H})} \tag{12}$$

2. **M-step:** estimate the distribution of the target state, x, from measurements, z, by marginalizing hidden variables, $\mathcal{H}$, that is

$$p(x|z) = \Sigma_{\mathcal{H}} p(x|z, \mathcal{H}) p(\mathcal{H}|\hat{x}, z) \tag{13}$$

4 Performance Analysis

To test the proposed system, the observation area is segmented into 64 blocks. The detection probability is $P_d = 0.825$. In order to achieve the best compression rate, a binary encoding scheme is developed. However, this encoding scheme can only guarantee each block code is unique. If a target triggers two blocks simultaneously, then the obtained code will be the combination of the two codes that represented these two blocks. Thereby the result will be a repetition of a single code. Obviously, the encoding scheme itself brings in false alarms. Technically, it is easy to remove the false alarms introduced by the scheme itself. Although

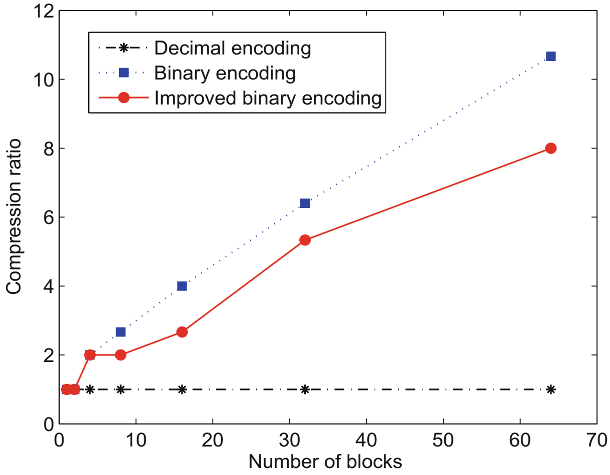


Fig. 5. Measurement compression ratio of various space encoding schemes.

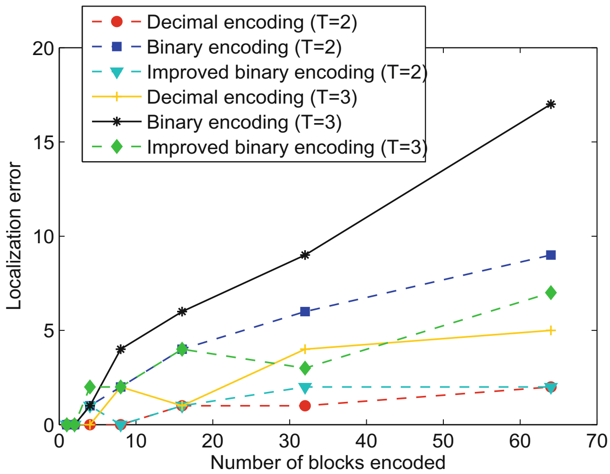


Fig. 6. Compressive localization for two-target and three-target cases.

the price is to increase the number of sensors, the number of sensors added is very small. Compared with decimal encoding, the number of sensors is still much smaller. Therefore, we can still guarantee a high compression rate. As shown in Fig. 5, for a 64-block area, the compression ratio of improved binary encoding is 8, which is close to the compression ratio of binary encoding 10.67 (ideal rate). The compression ratio of decimal encoding is 1, since there is no any compression in this encoding scheme.

Figure 6 shows the localization errors using various space encoding schemes for two targets case and three targets case, respectively. Although binary

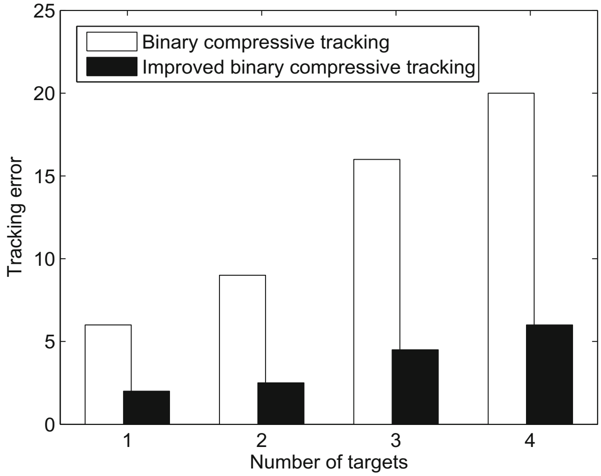


Fig. 7. Multi-target tracking performance.

encoding scheme can achieve the best compression rate, it has highest localization errors due to the ambiguities generated by the repetition of code patterns. In contrast, the improved binary encoding scheme has much lower errors. For the 64-block area, its localization error is just 2, which is much lower than that of binary encoding scheme at 9 for two targets case. When the number of targets increases to 3, the localization errors for all the encoding schemes become larger. It is reasonable since the data-target association becomes more difficult and complicated.

With multiplex sensing and space encoding, it is able to implement effective compressive multi-target tracking. Figure 7 shows the tracking performance of multiple targets via binary compressive tracking. It can be seen that (1) the binary compressive tracking errors are too large for real application, but the improved binary compressive tracking is acceptable with the average tracking errors at 4 and 6 for tracking three targets and four targets; (2) the increase of number of targets degrades the tracking performance of both schemes; (3) the improved binary compressive tracking scheme is more stable and scalable, with the growing of number of targets, its tracking error increases slightly and remains acceptable.

5 Conclusion

This work presents a new modality for wireless sensor based multi-target tracking tasks. The main feature of such a system is compressive tracking, which is easily achieved by using fiber-optic sensors. More specifically, compressive measurement is achieved by using multiplex sensing and space encoding technologies. Compressive tracking is implemented based on compressive localization and graphical model enabled tracking. The presented system is able to deal with complex tracking tasks in terms of false alarms, unknown data-target associations. The results demonstrate a good performance in tracking a small number of humans. The future work will be focusing on sampling geometry optimization and varying targets investigation.

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