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Multidimensional Scaling Based Location Calibration for Wireless Multimedia Sensor Networks

Rohit Kadam, Sijian Zhang, Qizhi Wang, Weihua Sheng

Abstract

Wireless Multimedia Sensor Networks (WMSNs) are gaining popularity among researchers over the past few years. Knowledge of the geographic locations of the sensor nodes is very important in a WMSN. In this paper we propose a new algorithm which uses the connectivity information, the estimated distance information among the sensor nodes, as well as the vision images to find the location of the sensor nodes to enable sensor calibration. We achieve this by solving an ID association problem in the WMSN. We then generate local maps for nodes in immediate vicinity and merge them together to get a global map. We demonstrate the effectiveness of our proposed approach through computer simulation.

Index Terms—**Wireless Multimedia Sensor Network, Sensor Localization, Camera Calibration, Multidimensional Scaling**

I INTRODUCTION

A. Motivation

Wireless Multimedia Sensor Networks (WMSNs) [1] are a research topic of growing interest over the recent years due to its wide applications. WMSNs are a set of wireless embedded devices that have the capability of processing and communicating video and audio streams collected from the environment in a distributed fashion [1]. WMSNs find applications in surveillance systems against crime and terrorist attacks. They can also be used for traffic monitoring in cities and highways. They are also very useful in military applications to locate the targets of interest (such as enemy soldiers, tanks) in the battlefield and relay video images to the command center.

For most WMSN applications, it is important to have the knowledge of the location of the nodes in order to understand the multimedia data received. Therefore, there is a great need to develop a sensor node calibration algorithm which can be implemented in embedded sensor nodes with limited computational resources.

Rohit Kadam and Weihua Sheng are with the School of Electrical and Computer Engineering, Oklahoma State University, USA. (contact:weihua.sheng@okstate.edu)

Sijian Zhang is with the College of Electrical Engineering, Zhejiang University, China.

Qizhi Wang is with School of Computer and Information Technology, Beijing Jiaotong University, China

In this paper, we are going to address this problem. We propose a new calibration algorithm using the network connectivity information and vision images. Based on the multidimensional scaling (MDS) technique [9,10] we derive node locations to fit the roughly estimated distances between pairs of nodes. We then use the information from the vision images to fuse it with the derived node locations in a distributed fashion.

B. Related Work

In recent years, researchers have been developing different sensor localization algorithms for wireless sensor networks. One kind of technique is based on inter-node distance ranging. To measure the distances, there are two basic techniques: received signal strength [4] and signal propagation time [5]. Given the inter-node distances, techniques like multilateration can be used to locate the nodes [6]. Range-free techniques have also been used widely. Hop number is used as an indication of the distance to the beacon nodes in some applications [7]. However, most of the literature is on localization of traditional wireless sensor networks and not much has been discussed on localization in wireless multimedia sensor networks, which have more sensing modalities than traditional ones.

Wireless Multimedia Sensor Networks can be understood as the convergence between the wireless communication networks and multimedia sensors such as cameras and microphones. The calibration of multimedia sensor nodes in WMSNs is very important. In existing literature, camera calibration has been widely researched in the computer vision community. Camera calibration involves the determination of the location and orientation of each sensor node [12, 13, 14]. Most camera calibration research is for a single camera and conducted in controlled laboratory environments. In [14], Kulkarni *et al*. propose a technique to determine the configurations of the camera sensor nodes where the camera nodes capture the images of an object of known size placed at various locations in the environment. Each camera node estimates its external parameters, the degree of overlap and region of overlap with its neighbors and uses this information to track the object. In [16], Lee and Aghajan present a collaborative technique to localize the nodes of a camera sensor network using opportunistic observations of a target.

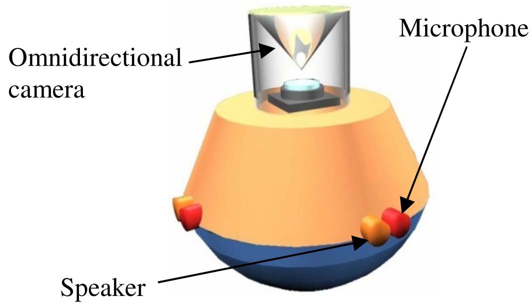

Fig. 1: The design of the multimedia sensor node.

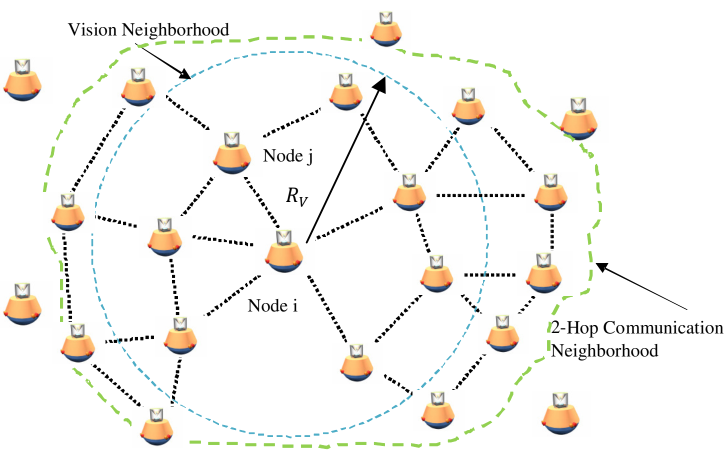

Fig. 2. The self-calibration of sensor nodes with respect to node *i*.

The cooperative target-based self-calibration protocol in [17] uses the target coordinate information at four locations in the field of view of a camera to perform calibration.

Overall, the existing camera calibration algorithms are either time-consuming, fit only in laboratory environments, or require specific cooperative or non-cooperative targets, which may not be realistic in many applications. The remainder of this paper is organized as follows. In Section II, we discuss the design of the wireless multimedia sensor nodes we are developing and formulate the WMSN location calibration problem. In Section III, IV and V we present the solution to this problem. We then discuss the simulation results in Section VI. Section VII concludes the paper.

II PROBLEM FORMULATION

We are developing a Wireless Multimedia Sensor Network for military surveillance applications. This surveillance network consists of a large set of sensor nodes which have omnidirectional vision, audio output, computation, and wireless communication capabilities. By forming a network they can provide battle-field awareness to military personnel. Below we will first introduce the design of the sensor node and then we will formulate the problem of location calibration in this WMSN.

The proposed WMSN consists of a network of homogeneous sensor nodes which serve to enhance a soldier's auditory and visual fields. As shown in Fig. 1, each sensor node is outfitted with an omnidirectional video camera, an array of microphones, a compass, modest computing resources (PDA-level CPU), and wireless communication capabilities (250 Kbits/sec data rate). The sensor nodes can be deployed by soldiers, ground vehicles or airplanes. The sensors have the ability to self-organize in the sense that the sensor calibration and the establishment of communications will be performed autonomously. The form-factor of the sensor is relatively small so that they can be easily carried and deployed. The dimension of the sensor is close to that of a human fist and its weight is less than two pounds.

We consider n multimedia sensor nodes randomly deployed in a region as shown in Fig. 2. The node N_i has two neighborhoods defined, as can be seen in Fig 2. N_i can communicate with its neighbors and form a *communication neighborhood*. Similarly, node N_i can see the neighbors through its omnidirectional camera. These nodes form its *vision neighborhood*. We assume that each node can measure the distance to its one hop neighbor in the communication neighborhood. Such a capability can be realized through the Time Difference of Arrival (TDoA) technique, which is based on the time difference between an acoustic signal and a RF signal when they both travel from one node to the other.

The problem of location calibration in a WMSN is to find the relative locations of all the nodes in the deployed sensor network. If we have at least three beacon nodes we can find the absolute locations of all the nodes in the deployed network. In this work we make the following assumptions:

1. There are no obstacles in the region described, so any sensor nodes within a distance R_v to N_i can be observed by N_i.
2. Each sensor node can find its orientation through onboard compass so that the orientations of the sensor nodes are known.

III OVERALL APROACH FOR LOCATION CALIBRATION

To solve the above sensor location calibration problem, we need to solve a *local map generation* problem for each individual sensor node and then solve the map merging problem to get the global map of sensor locations.

In the local map generation problem, each node first obtains a vision map from the omnidirectional image and then estimates the location of each neighboring node within the vision range R_v. However, since all the sensor nodes have the same shape and color, their IDs cannot be determined on this vision map, which means that the vision map provides us with the information of relative location of the nodes with a reasonable accuracy but no ID information. Next, each node generates an ID map using the multidimensional scaling (MDS) algorithm. Since each node can measure the distance to its neighbors in the one-hop communication neighborhood, it can construct a distance matrix for its 2-hop communication neighborhood and feed it to the MDS algorithm to create a relative map of IDs. However, the MDS algorithm is not very accurate since it depends on the shape of the network topology and the density of the network. Therefore the ID map only provides us with the information of the node IDs but not accurate information of the relative location of the nodes. In this sense, the ID map and the vision map complement each other. Therefore, the local map generation problem is essentially an ID association problem, that is to associate the IDs in the ID map to the vision map. To solve the ID association problem, we propose an algorithm based on the iterative closest point (ICP) algorithm [11].

We then solve the map merging problem. We do this by searching for the next best node to merge with the initial arbitrarily selected node (base node) and thus expand its local map. The next best node is the one with a local map that has the maximum number of unknown IDs and minimum but not less than three common IDs. Then we merge these two maps together. This process is repeated until all the nodes in the network are covered. The overall algorithm for the location calibration is summarized as follows:

1) Each node generates a local map by solving the ID association problem.
2) Select an arbitrary node as the base node N_b.
3) Search for the next best node as a candidate for merging from the nodes in the current partial global map of N_b and request for the local map from the node selected.
4) Merge the maps for node N_b and the selected node. Update the current partial global map for N_b and repeat steps 3 and 4, until all the nodes in the entire network are localized.

IV LOCAL MAP GENERATION

A. Vision map generation

Each node takes an image of the environment using its embedded omnidirectional camera. From this image it gets the distance and angle information of each of its vision neighboring node. The distance information can be calculated based on the size of the image of the sensor node (x, y) [18]. We assume that the distortion correction on the omnidirectional images has been done. Based on the above information, we can estimate the location of each node within the vision neighborhood. A typical vision map is shown in Fig. 3.

B. ID map generation

Multidimensional Scaling (MDS) algorithm is a popular statistical tool used to depict the dissimilarities or proximities between the objects through a placement of points in a low-dimensional plane where the Euclidean distances between the points resemble the actual generate a distance matrix which is a dissimilarity measure for the sensor nodes within a two hop communication neighborhood. The MDS algorithm can plot these points with origin as the centroid.

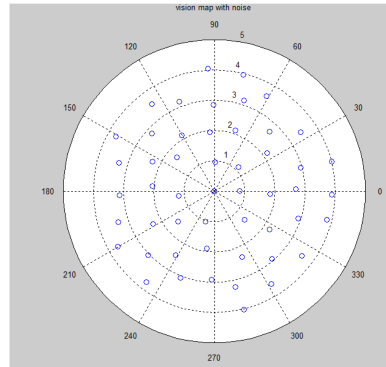

Fig. 3: A typical vision map.

Based on the classical MDS, our method to generate the ID map consists of four steps:

1) Collect the connectivity and distance information within the two-hop communication neighborhood of the node.
2) The shortest path between each pair of nodes is computed. A node can measure distances to its neighbors only, and for the rest of the nodes which fall outside the communication range, an "infinite" value is assigned as the distance.
3) Floyd's Algorithm is used to compute the shortest paths between any pair of nodes using the connectivity information.
4) The distance matrix obtained in the above step is input to the Classical MDS (CMDS) algorithm which constructs a relative map with two dimensions. An optional refinement step involving least-squares minimization can be included to best conform to the inter-distances of the nodes to the measured distances.

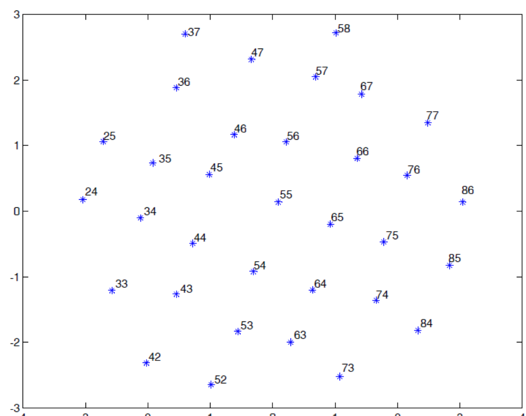

Fig 4. A typical ID map .

The performance of classical MDS based localization is determined fundamentally by the network topology parameters. It is observed that the density of the network has a direct relationship with the performance. Denser networks exhibit less mean localization error. The second distinctive performance parameter is the shape of the network topology. If the nodes are deployed in a regular pattern, the results are better. Through the above three steps, an ID map is generated in the two-hop neighborhood, which will be associated with the vision map of that node.

C. ID Association Algorithm

We propose a map registration approach to solve the ID association problem. This approach has two steps. In step 1, we conduct a pre-registration to roughly align the ID map with the vision map. In step 2, we refine the registration with the ICP algorithm.

Step 1: Pre-registration

In this step we associate the nodes in the vision map (x_V, y_V) and ID map (x_m, y_m) to find the best possible correspondence. This is done by searching the global minimum angle which can give the rough association.

To find the global minimum angle, we perform the following steps:

1. Translate the ID map in order to have an overlapped centroid with the vision map.
2. For $\emptyset$= 1:360 with increment of 1 degree do:

- *Rotate the ID map by $\emptyset$ degree;*
- *Calculate the corresponding pairs between the nodes in the ID map and the vision map based on the closest distance.*
- *Calculate the sum of the square of the distances between the corresponding pairs and find the minimum sum and its $\emptyset$.*

$$min \sum((x_V - x_m)^2 + (y_V - y_m)^2)$$

3. Calculate the rotation matrix:

R_pre=$[cos\,\emptyset, sin\,\emptyset;\ -sin\,\emptyset, cos\,\emptyset]$

4. Generate the new ID map:

*ID_new = R_pre *ID*

Through the above steps, the ID map is rotated and brought close to the vision map, which will be further rotated in Step 2 for refinement.

Step2: ICP based refinement

After the nodes in the vision map and relative ID map have been roughly associated in the above step, we run the iterative closest point algorithm [11] to refine the correspondence of the two maps to a higher degree of accuracy. The ICP algorithm finds the rotation and translation matrix between the preregistered ID map and the vision map by minimizing the least square errors among the closest node pairs. Based on the refined registration, we can identify the correct ID association between the nodes in the ID map and the vision map.

V MAP MERGING

Each node has its local map after solving the ID association problem as discussed above. Then we address the problem of merging or growing the local maps by obtaining the best linear transformation to transform the coordinates of the common nodes in one map to those in the neighboring map. This enables us to localize all the nodes in the network. We call this *the map merging algorithm.*

We define the following variables:

M_b : $\{(x,y)_b, ID_b\}$ is the partial global map of node N_b.

ID_b: The IDs in the local map of N_b

$(x,y)_b$: The local map coordinates of node N_b

N_j : The next best node selected for merging

M_j : $\{(x,y)_j, ID_j\}$ is the local map of node

ID_j : The IDs in the local map for the next best node N_j

$(x,y)_j$: The local map coordinates for the node N_j.

$(x,y)_j^b$: The local map coordinates for node N_j in node N_b coordinate frame.

The following steps are involved in the map merging algorithm:

1. For base node N_b, find the neighboring node that has a local map with the maximum number of unknown IDs and minimum number of three common IDs.
2. Request for the local map from the selected node.
3. Find the linear transformation by using the Procrustes function. Transform the next best node map M_j into node N_b's coordinate frame to get M_j^b using:

$$(x,y)_j^b = (x,y)_j * \begin{pmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{pmatrix} + (T_X \quad T_Y)$$

where R is a combination of the rotation and reflection factor and T is the translation factor.
4. Update the partial global map M_b using

$$M_b = M_b \cup M_j^b$$

5. Repeat the steps 1-4 and thus update the partial global map until it contains all the nodes.

VI SIMULATION RESULTS

A. Simulation Setup

We conducted computer simulation to evaluate the proposed approach. The simulation is carried out in MATLAB. The PC used is a standard Dell Inspiron with an INTEL core 2 Duo T5750 @ 2GHz processor and a 3GB RAM. In our simulation, nodes are placed in a square area. We model the placement errors as Gaussian noises [5]. We place the nodes in a square grid with placement errors. For a given placement error e_p, we draw a random value from the normal distribution $r \times e_p \times N(0,1)$. This value is added to the nodes original grid position. In this way, we can create a random sensor distribution mimicking, for example, airplane deployment. One hundred nodes are placed on a 10r x 10r grid; with a unit edge distance *r*. Figure 5 shows an example of the deployment with 10% placement error. The radio range is R = 1.99r, which leads to an average connectivity of 8.14. In the graph, the points represent the sensor nodes and the edges represent the one-hop connectivity between neighbors.

B. Results

Figure 6 shows the result of the ID map (green circles)

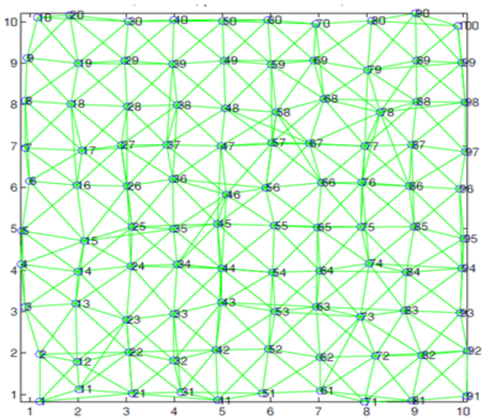

Fig. 5: The ground truth of the sensor deployment (100 nodes, R=1.99r, placement error=10%)

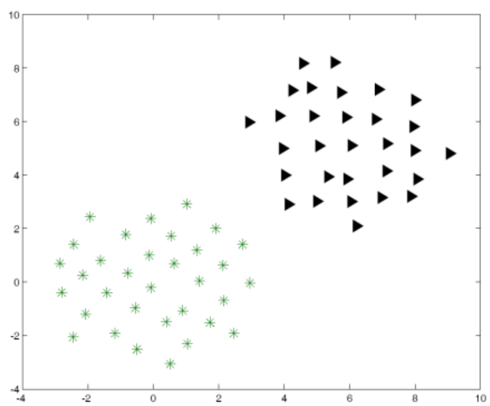

Fig. 6: The ground truth for vision map (green circle) of the sensor nodes and the ID map obtained (black triangles).

based on the two-hop communication neighborhood of the base node. It can be seen that the center of the ID map is the origin (0, 0), and it has a different orientation than the original network. Fig. 7 shows the result after performing pre-registration and associating the IDs in both the ID map and the vision map. It can be seen that there is still a significant distance error between the corresponding pairs in the two maps. In Figure 8, the result shows the IDs in the ID map match the ground truth IDs of the vision map after performing the ICP refinement algorithm.

In Table 1 we have listed the mean square error (MSE) of the locations in the vision map and the ID map. This table summarizes the results for various radio ranges. The average degree of connectivity for radio range up to 1.5R is greater than 5 and the noise in the placement error is 10% Gaussian noise. This shows that with the increase of the radio communication range, the ID map results will be better and the registration error will be smaller.

The merging of the maps has been carried out by selectively choosing the next node. Figure 9 shows an example of local map for base node 55 merged with local map for node 37 when the vision range selected is 3.1. It can be seen that the node 37 is the best candidate for merging since it has maximum (18) unknown nodes and at least three

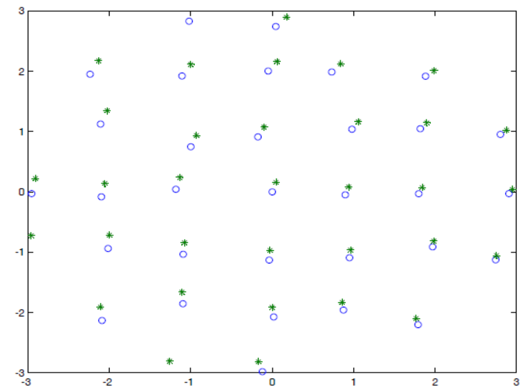

Fig. 7 ID Association using pre-registration. The nodes in the vision map are brought close to the nodes in the ID map.

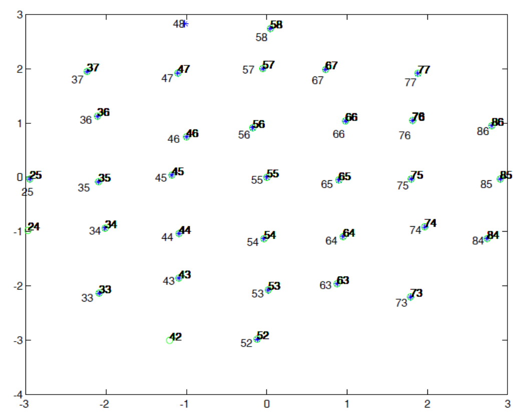

Fig. 8. The map shows the correct ID association between the ID map and the vision map after performing the ICP refinement algorithm. The IDs shown on the figure indicate that they have the perfect match.

common nodes. Figure 10 shows a final global map for the randomly selected node 55. Table 2 shows the MSE for variations introduced in the placement errors. The mean square error for the placement error increases as more noise is introduced in the placement of the nodes.

In summary, we find that the ID association results are good for an average connectivity of 8. Hence application scope is limited to average network connectivity greater than 8 for grid based networks. When the network is sparse average degree of connectivity is below 8; the ID map results are found to be bad, which will cause wrong ID association as tabulated in the table 1.

TABLE 1

MEAN SQUARE ERROR OF THE LOCATIONS IN THE VISION MAP AND THE ID MAP R=1.99r. $R_V = 3.1$

Noise	10%	10%	10%	10%	10%
Radio Range	2R	1.75R	1.5R	1R	0.75R
MSE	0.0176	0.0988	0.1057	3.885	4.605
ID association	correct	correct	correct	incorrect	incorrect

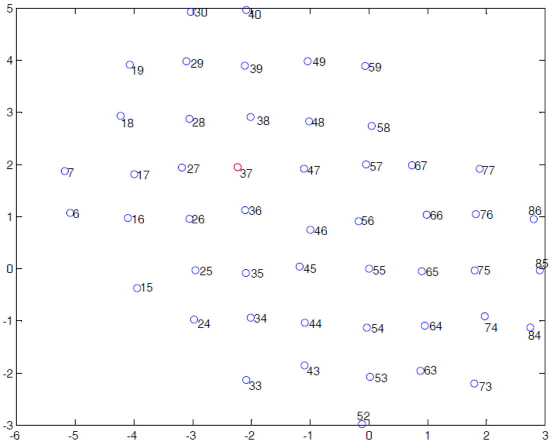

Fig 9. The above figure illustrates merging of local map of node 55 with local map of node 37.

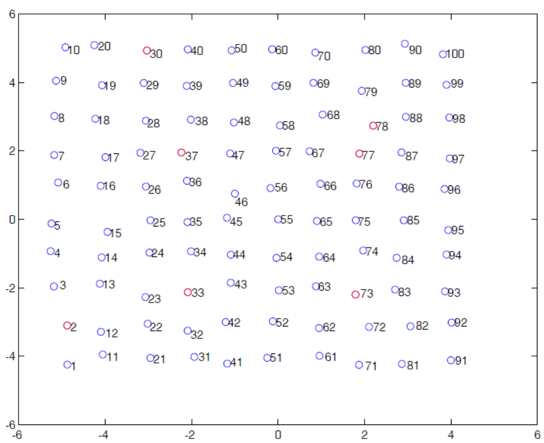

Fig. 10: The global map for base node 55.

TABLE 2
MEAN SQUARE ERROR FOR VARIOUS PLACEMENT ERRORS (NOISE) FOR A SELECTED VISION RANGE OF 3.1 RADIO RANGE OF R=1.99R

Noise (%)	MEAN SQUARE ERROR
5	0.0298
10	0.0309
15	0.0336
20	0.0459

VII CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a solution to the location calibration problem in wireless multimedia sensor networks. Our proposed solution consists of two parts. In the first part, the local map generation algorithm is explained. The second part discusses the map merging algorithm. The local map generation algorithm consists of three steps. In step one; a local vision map is generated. Then in step two, the ID map is generated based on the MDS algorithm and in step three, the ID association problem is solved based on the ICP algorithm. In the second part we explained the map merging algorithm. The map merging algorithm consists of finding the next best node and then merging the partial global map and the selected map by finding the best possible linear transformation between the coordinates of these maps. We evaluated the proposed approach through computer simulations. This location calibration algorithm can be used to develop self-organized wireless multimedia sensor networks, which can have great potentials to be used in surveillance and monitoring applications.

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