Simultaneous View and Feature Selection for Collaborative Multi-Robot Recognition

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Abstract—Collaborative multi-robot perception provides multiple views of an environment, offering varying perspectives to collaboratively understand the environment even when individual robots have poor points of view or when occlusions are caused by obstacles. These multiple observations must be intelligently fused for accurate recognition, and relevant observations need to be selected in order to allow unnecessary robots to continue on to observe other targets. This research problem has not been well studied in the literature yet. In this paper, we propose a novel approach to collaborative multi-robot perception that simultaneously integrates view selection, feature selection, and object recognition into a unified regularized optimization formulation, which uses sparsity-inducing norms to identify the robots with the most representative views and the modalities with the most discriminative features. As our optimization formulation is hard to solve due to the introduced non-smooth norms, we implement a new iterative optimization algorithm, which is guaranteed to converge to the optimal solution. We evaluate our approach on multi-view benchmark datasets, a case-study in simulation, and on a physical multi-robot system. Experimental results demonstrate that our approach enables accurate object recognition and effective view selection as defined by mutual information.

I. INTRODUCTION

Collaborative multi-robot perception enables a group of robots to combine their individual observations to collectively gain a unified understanding of the environment [1]. Multi-robot systems can provide multiple observations of objects, and usually enable views of the objects from different points of view. In real-world scenarios, such as in disaster response and search and rescue applications [2], [3], individual robots can have their views occluded or sometimes fully obstructed by obstacles and other environmental factors. Collaborative perception can rely on the observations that contain the most representative views of objects obtained from multiple robots to effectively and collaboratively perceive the objects despite the limitations of individual robots.

We address the collaborative multi-robot perception problem of recognizing an object from multiple views provided by a collection of robots operating around the object in the environment. This perception problem becomes collaborative as the observations from multiple robots equipped with a variety of sensors need to be combined into a unified understanding of the object. Effectively fusing multi-modal observations from multiple robots relies on the identification of the most informative views and modalities. It not only increases the accuracy of object recognition, but also enables robots to be distributed where they are most useful. For example, robots behind obstacles can be assigned elsewhere, or robots equipped with LiDaR sensors can be assigned to dark areas while those with only visual cameras can be used in an environment with good lighting conditions.

Previous research has investigated both recognition from multiple views and discriminative sensor and view selection. Multi-view recognition methods were developed to recognize objects [4], gait [5], and actions [6] from multiple points of view. The previous approaches are generally based on visual features manually engineered for their specific applications. Sensor and view selection has been studied in different ways, e.g., based on sparse coding [7] and uncertainty reduction [8], and applied to sensor placement and path planning in order to maximize observations. However, view selection and feature modality selection are treated as two independent procedures. The key research problem of how to enable both in a unified approach has not been well addressed, especially in the area of collaborative perception for object recognition.

In this paper, we introduce a novel approach to collaborative multi-robot perception that enables object recognition from multiple views of a group of robots while simultaneously enabling selection of discriminative views and features. We propose a formulation based on regularized optimization that identifies the combination of views that best represents and recognizes objects, providing a unified framework that incorporates recognition, view selection, and feature selection. Through the introduction of structured sparsity-inducing norms as regularization terms during the optimization, we identify both the robots with the most representative views, as well as

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the most discriminative feature modalities. Due to non-smooth norms and parameter dependence, our formulated regularized optimization is hard to solve. We implement a new iterative solver, which we prove is theoretically guaranteed to converge to the optimal solution. We perform extensive evaluation, utilizing multi-view datasets, a high-fidelity robotics simulator, and a physical multi-robot system. Experimental results show that our approach achieves both accurate recognition as well as effective view selection, and shows the effectiveness of our proposed regularization terms.

This paper has two key contributions:

- First, we introduce a principled approach to collaborative multi-robot perception which unifies multi-view object recognition, view selection, and feature selection into a single formulation based on the mathematical framework of regularized optimization.
- Second, we implement a new iterative solution algorithm to solve the proposed formulation, which has a theoretical guarantee to converge to the optimal solution.

II. RELATED WORK

A. Multi-Robot Perception

Our proposed work closely aligns with the research problem that optimally places and controls robots based on their observations. Many methods attempt only the placement of fixed sensors to maximize observations [9]–[11]. However, many others work to coordinate multiple robots to maximize sensor coverage, such as with power- and capability-limited robots used in swarms [12], or to identify corresponding objects between observations [13]. Similar approaches work by dividing swarms into subgroups to maximize the monitoring of multiple areas of interest [14], deploying [15] or dividing [16] heterogeneous teams of robots based on their sensing capabilities, or attempting to merge sensor observations to provide ‘collective perception’ [1]. In contrast to these approaches, we formulate our method to integrate object recognition as well as identifying the individual robots with the most discriminative observations. By identifying the robots with the most representative views as they are observing a target and the most discriminative sensing modalities, we allow the remainder of the robots to continue on to other tasks.

Another relevant research area is active perception, with the objective to adjust sensor positions and settings to obtain optimal views of objects [17]. In multi-robot systems, active perception has been applied to navigation planning and target tracking. Navigation planning approaches apply active perception as a reward or constraint, where paths that involve the most observations of areas are rewarded [18], [19]. Target tracking approaches apply active perception to the goal of observing a single or set of targets as opposed to observing an area. Approaches have been based on Kalman filters [20], scheduling algorithms [21], and entropy measures [22].

In computer vision applications, multi-view perception has been applied to a variety of recognition tasks, utilizing fixed sensors or cameras. Multi-view recognition has been applied to object recognition [4], [23], gait recognition [5], and action recognition [6]. Multiple views typically increase recognition accuracy, but can also incur a high computation cost. Because of this challenge, approaches have been developed to narrow down the number of views and identify the views that can best represent objects [24], [25]. Several methods were also designed to select the 2D views that best reconstruct a 3D model [26]–[29]. Methods were also implemented to identify objects from multiple cameras, including search algorithms [30], convolutional neural networks [31], and semantics [32].

B. Feature Selection

Similar to our goal of identifying the most discriminative views among a group of robots, many approaches have been developed to select features [33] and sensors that minimize redundancy while maximizing information. Feature selection approaches identify the most discriminative features, either as a problem of dimensionality reduction or to identify the certain features that correspond to specific situations. This has been done by selecting features that reduce uncertainty in a graphical model [7], utilizing sparsity to identify feature modalities that best describe an environment [34], learning weights of different features [35], or evaluating information content to avoid selecting redundant features [36].

The selection of discriminative sensors in sensor networks has been studied from a variety of directions [37]. For target tracking, sensors can be chosen based on their capabilities of location [38], [39] or to best provide coverage of an entire area [40]. Selection methods have also been introduced based on task allocation algorithms [41], sparsity [8], [42], cross entropy [43], and even randomized algorithms [44], [45].

The previous multi-view recognition and feature selection approaches generally treat view section and feature modality selection as two separate and independent procedures. The problem of how to address both in a unified approach has not been well addressed, especially in the area of collaborative perception for object recognition.

III. OUR PROPOSED APPROACH

In this section, we introduce our approach to collaborative perception using an optimization-based formulation that unifies recognition and the selection of discriminative views and feature modalities.

Notation. In this paper, we denote matrices using boldface uppercase letters and vectors using boldface lowercase letters. For a matrix $M = \{m_{ij}\}$, we denote its $i$-th row as $m_i$ and its $j$-th column as $m_j$. The $\ell_1$-norm of a vector $v \in \mathbb{R}^n$ is $\|v\|_1 = \sum_{i=1}^{n} |v_i|$ and the $\ell_2$-norm is $\|v\|_2 = \sqrt{\sum_{i=1}^{n} v_i^2}$.

A. Problem Formulation

We define the problem of collaborative multi-robot perception as combining the available views from a group of robots in order to identify an object. Our formulation learns a linear combination of views to represent a given object, fusing the visual features from each to identify the object that they best represent, based on the value of the final objective function.

Formally, we define the observations from $n$ robots as $X = [x^1, \ldots, x^n] \in \mathbb{R}^{n \times d}$, where $x^i \in \mathbb{R}^d$ is the feature vector.
denoting the observations of the $i$-th robot. As each robot can utilize multiple sensors or describe observations as multiple forms of feature representations, each vector $x^j$ contains representations from $m$ modalities, where $d = \sum_{j=1}^{m} d_j$. We denote $p$ categories of objects as $O = \{o_1, \ldots, o_p\} \subset \mathbb{R}^{d \times p}$, where $o_j \subseteq \mathbb{R}^d$ is a feature vector representing the $j$-th object. Objects are encoded with the same feature types that are able to be utilized by the robots, defined from a single view of an object (e.g., if robots represent their observations with a histogram of RGB values, then each object is encoded with the same type of histogram formed from a representative view of the object). Then, we formulate object recognition in our collaborative multi-robot perception approach with the following loss function:

$$
\min_w \|X^T w - o_j\|_2^2
$$

(1)

where we approximate each object $o_j$ for $j = 1, \ldots, p$ through a linear combination of the available views from the multi-robot system. The views are weighted by the weight vector $w \in \mathbb{R}^n$, where $w_i$ represents the importance of the $i$-th robot's view in approximating the object.

**B. Learning Discriminative Views and Modalities**

When a group of robots are observing an object, a subset of robots will have more representative views of the object, and certain feature modalities will be much more informative than others. We introduce regularization terms in our formulation to identify the robots with the most discriminative views and the most relevant features.

First, we learn the most informative views, both to rely on them for accurate recognition and to identify the robots with the best views, so that the remaining robots can continue on in the environment to perform other tasks. To do this, we introduce $\|w\|_1$, utilizing the $\ell_1$-norm on the weight vector $w$. This regularization term induces sparsity in this weight vector, forcing most values to 0 or very small values near 0 and limiting high weights to the most discriminative views. With this, our formulation is

$$
\min_w \|X^T w - o\|_2^2 + \lambda \|w\|_1
$$

(2)

where $\lambda$ is a hyperparameter controlling the importance of this sparsity-inducing norm.

Second, we learn the most discriminative feature modalities, not only to further improve recognition accuracy, but also to identify the sensing modalities that are most useful in the environment - i.e., due to varying lighting conditions and views between known objects and observations, certain modalities and representations could be significantly more informative. To achieve this, we introduce a weight vector $u \in \mathbb{R}^d$, which denotes the importance of each feature modality to the view weight vector:

$$
\|Xu - w\|_2^2
$$

(3)

This loss-like function influences the learning of $w$, by incorporating the weighting of individual features. It also enables us to identify the importance of each feature modality, as $u = [u^1, \ldots, u^m]$ where $u^i \in \mathbb{R}^{d_i}$ specifically represents the importance of the $i$-th feature modality to the view selection weights in $w$.

Then, to identify the discriminative feature modalities, we introduce a group $\ell_1$-norm applied to $u$ as the regularization, which is termed the *modality norm*:

$$
\|u\|_M = \sum_{i=1}^{m} \|u^i\|_2
$$

(4)

This regularization term utilizes the $\ell_2$-norm within feature modalities and the $\ell_1$-norm between modalities. The $\ell_2$-norm causes weights within a modality to become similar, while the $\ell_1$-norm induces sparsity between them, causing only the most discriminative modalities to have non-zero weights.

With these two regularization terms to identify discriminative views and feature modalities, respectively, the proposed final problem formulation becomes:

$$
\min_{w,u} \|X^T w - o\|_2^2 + \|Xu - w\|_2^2 + \lambda_1 \|w\|_1 + \lambda_2 \|u\|_M
$$

(5)

where $\lambda_1$ and $\lambda_2$ are hyperparameters that control the importance of the regularization terms.

This optimization problem is calculated for each object. The recognized label of a given object is the category that has the lowest value of the objective function, since it is best represented by the multiple views. This proposed formulation simultaneously integrates view and feature selection, as well as object recognition into the unified regularized optimization framework, without requiring a separate classifier for object recognition.

**C. Optimization Algorithm**

Due to the non-smooth norms utilized to identify the most representative views and most discriminative features and the interdependence of the $w$ and $u$ weight vectors, our formulation is hard to solve. We introduce an iterative algorithm to solve the formulation in Eq. (5), which alternately solves for $w$ and $u$ at each iteration until convergence. We show that our approach is theoretically guaranteed to converge to optimal values for the weight vectors.

First, we solve $w$ by taking the derivative of the objective function with respect to $w$ and setting it to 0:

$$
2XX^T w - 2Xo - 2Xu + 2Iw + \lambda_1 D^w w = 0
$$

(6)

Here, $I$ is the identity matrix and $D^w \in \mathbb{R}^{n \times n}$ is a diagonal matrix where the $i$-th diagonal element is $\frac{1}{\lambda_2}$, corresponding to the partial derivative of $\|w\|_1$. After rearrangement, we see that $w$ is updated by

$$
w = \left(XX^T + I + \frac{\lambda_1}{2} D^w\right)^{-1} X (o + u)
$$

(7)

Second, we now solve for $u$ by taking the derivative of the objective function with respect to $u$ and setting it equal to 0:

$$
2X^T Xu - 2X^Tw + \lambda_2 D^u u = 0
$$

(8)

where $D^u$ is a block diagonal matrix corresponding to the partial derivative of $\|u\|_M$, with its $i$-th block as $\frac{1}{2\|u_i\|_2} I$. 
Algorithm 1: Our iterative algorithm to solve the formulated regularized optimization problem in Eq. (5).

\begin{algorithm}
\small
\textbf{Input}: $X = [x^1; \ldots; x^N] \in \mathbb{R}^{n \times d}$, \\
$O = [o_1, \ldots, o_p] \in \mathbb{R}^{d \times p}$.
\textbf{Output}: $o^*$ (the recognized object) and $w^*$ and $u^*$ (weight vectors identifying the most representative views and discriminative features).
\begin{enumerate}
\item \textbf{foreach} column vector $o$ in $O$ \textbf{do}
\item Let $i = 1$. Initialize $w$ by solving Eq. (1) and $u$ by then minimizing Eq. (3).
\item \textbf{repeat}
\item Calculate $D^w(i + 1)$, where the diagonal is equal to $\frac{1}{2w(i)}$.
\item Calculate $D^u(i + 1)$, where the $j$-th diagonal block is equal to $\frac{1}{2(u^{(i)}(j))_2}I_j$. \hfill (7)
\item Calculate $w(i + 1)$ via Eq. (5).
\item Calculate $u(i + 1)$ via Eq. (9).
\item $i = i + 1$.
\item until convergence;
\item Compute the value of Eq. (5) using $w(i)$ and $u(i)$.
\item if objective value is lowest then
\item $o^* = o$, $w^* = w(i)$, $u^* = u(i)$
\item end \end{enumerate}
\item \textbf{return} the recognized object $o^*$ and the associated $w^*$ and $u^*$.
\end{algorithm}

where $u^i$ is the section of the weight vector $u$ corresponding to the $i$-th modality and $I$ is an identity matrix with appropriate dimensions for $u^i$. We rearrange it to see that $u$ is updated by

$$u = \left( X^\top X + \frac{\lambda_2}{2} D^u \right)^{-1} X^\top w$$ \hfill (9)

In each update step, we assume that the other weight vector is fixed (e.g., in Eq. (7) we treat $u$ as fixed from the previous iteration). We alternate these update steps until the values of each variable converge. Algorithm 1 details our implemented optimization solver. In the following, we show that our proposed algorithm theoretically converges to the optimal solution.

\textbf{Theorem 1}: The inner loop of Algorithm 1 is guaranteed to converge to the optimal solution to the formulated regularized optimization problem in Eq. (5).

\textbf{Proof}: See supplementary materials. \hfill \blacksquare

The time complexity of Algorithm 1 is dominated by Steps (6) and (7) in each iteration. Steps (4) and (5) are trivial, being only linear in complexity. Steps (6) and (7) each require a matrix inverse, which could be solved as a system of linear equations as opposed to explicitly finding the inverse, and so respectively require $O(n^2)$ and $O(d^2)$ to solve. As typically $d \gg n$, our approach’s complexity is bounded by the dimensionality of features chosen, and not the number of robots.

\section{IV. Experimental Results}

To effectively assess the performance of our proposed collaborative multi-robot recognition approach, we evaluated on existing multi-view benchmark datasets, conducted a case study in a high-fidelity robot simulator, and executed our approach on physical robots. We also discuss the effect of the hyperparameters $\lambda_1$ and $\lambda_2$.

In all of our experiments, we utilize three feature modalities. First, we utilize a color histogram, based on the RGB values of each pixel. Second, we utilize a Histogram of Oriented Gradients (HOG) \cite{Dalal05} to describe the shape of the observation. Finally, we describe the textures in an observation using Local Binary Pattern (LBP) features \cite{Ojala02}. Each observation is described fully, i.e. the object to be recognized is not defined by a bounding box from labeling or detection. This enables us to evaluate our approach as it would actually be used in the real world, where object detection is unavailable on computing-limited robots.

\subsection{A. Evaluation on Multi-View Benchmark Datasets}

Our approach was first evaluated on two existing datasets to determine its performance on an object recognition task. We utilize these datasets as there currently is a lack of multi-view datasets based on observations from multiple robots.

- Columbia University Image Library (COIL) \cite{Lowe03}: This dataset consists of 20 various household objects in grayscale with the background removed and the image cropped so the object fills the frame. Each object is rotated 360 degrees, with an image captured approximately every five degrees, resulting in 72 views for each object. Sample objects can be seen in Figure 2.

- 3D Reconstruction Multi-View Dataset (3DRM) \cite{Cremers08}: This dataset consists of five 3D models of objects rendered in color and captured from various views, including from above. Each object is captured between 20 and 35 times, with an average of 29 views per object. Sample objects from this dataset can also be seen in Figure 2.

For each object in each of the datasets, a single image was selected as the object’s known representation, and removed from the set of possible inputs. For COIL, this was the first image in each sequence. For 3DRM, this was a front view of the object. All the other images of each object were considered views of that object.

Figures 2(a) and 2(b) show the recognition results on these two datasets for various hyperparameter values, as increasing portions of available views are used. We perform multiple testing iterations based on random selections of available views, from a single view to all available views. We see that in both datasets, our approach performs worst when the hyperparameters controlling the values of our regularization

\begin{thebibliography}{1}
\bibitem{COIL} The COIL benchmark dataset is publicly available at \url{http://www1.cs.columbia.edu/CAVE/software/softlib/coil-20.php}.
\bibitem{3DRM} The 3DRM dataset is available at \url{https://vision.in.tum.de/data/datasets/3dreconstruction}.
\end{thebibliography}

B. Evaluation in Simulation and on Physical Robots

We next performed a case-study evaluation in a high-fidelity simulator, which allowed for the simulation of real robots and sensors through a ROS interface. We chose three different objects: two cars, in which the known reference view was from the side, and a large sign, with the known view being straight on. Qualitative results from this can be seen in Figure 4, which shows the top three views from each different scene as ranked by our approach. We can see that our approach is able to select the Husky robots which have qualitatively good views of each object, allowing the other robots to continue on to other tasks.

Finally, we evaluated our approach on a physical multi-robot system. This system consists of an overhead camera for robot tracking and six robots, each using a Raspberry Pi 3+ for on-board computing and equipped with an RGB camera. The set of objects consisted of eight toys of varying size, shape, and color, with a selection seen in Figure 5(a). For each object, multiple sets of data were collected with a varying amount of obstructions by obstacles. Robots were positioned surrounding the object, with views that were either unobstructed, partially obstructed to different degrees, or fully obstructed. An overhead view of this setup can be seen in Figure 5(a).

Quantitative results on recognition are reported in Figure 2(c). We evaluate four versions of our approach, by setting $\lambda_1$ and $\lambda_2$ to either 0 or 0.1 (for both a baseline analysis and an optimal parameter setting, described later in Section V-C). We evaluate our approach by selecting a random subset of $n$ views, from a single view to all six views, and repeat this 10 times for each value of $n$. We observe consistently that when any number of views are used, setting $\lambda_1 = \lambda_2 = 0$
Fig. 4. We conducted our case-study in a high-fidelity robot simulator with three objects – the red car, the gray car, and the sign seen in these overhead scenes. The three best views from the multi-Husky system as ranked by our approach are shown beneath each overhead scene.

![Multi-Robot Views](image1)

(a) Multi-Robot Views

![Weight Vector w](image2)

(b) Weight Vector w

![Weight Vector u](image3)

(c) Weight Vector u

![λ1 and λ2](image4)

(d) λ1 and λ2

Fig. 5. These figures show the effect of our two introduced sparsity-based regularization terms to identify the most representative views and the most discriminative features. Figure 5(a) shows a testing iteration of the multi-robot system observing an object, with the six robot views. Figures 5(b) and 5(c) show the associated weight vectors indicating the weights assigned to various robots and features. Figure 5(d) quantifies the effect of various hyperparameter values controlling the importance of the two regularization terms.

performs the worse compared to any other set of parameters. Similarly, recognition accuracy is consistently at its highest when $\lambda_1 = \lambda_2 = 0.1$, achieving the best recognition for each set of $n$ views. This demonstrates the value of our two introduced regularization terms. We also observe that when using only one of the sparsity-inducing norms (i.e., setting one $\lambda$ parameter to 0.1 and the other to 0) we see better performance when using $\|w\|_1$, forcing the use of the most representative robots. This result indicates that relying on a better view provides more accurate recognition than better features in random views.

C. Discussion

**Discriminative View and Feature Modality Selection.** We evaluate the performance of view and feature selection enabled by the two regularizing norms we introduce. Figures 5(b) and 5(c) show the distribution of weights for the testing iteration seen in Figure 5(a), where six robots observe the helicopter object from Figure 3. In this test, an obstacle is completely obstructing one robot’s view and partially obstructing the view of a second. The four remaining robots have unobstructed views of the object, but from varying angles. We see values of nearly 0 assigned to the two obstructed views in w, with small values assigned to two other poor views of the target object. Over 80% of weights are assigned to two views, identifying these as the most representative of the target. In u, we observe that the total weight for the LBP features is nearly 0, with HOG features being the primary discriminative modality for this setup. Both figures demonstrate the effectiveness of the induced sparsity in identifying a small number of representative views and discriminative modalities.

**Hyperparameter Analysis.** We also evaluate the effect of the hyperparameters $\lambda_1$ and $\lambda_2$, which control the importance of these sparsity-inducing norms, on the recognition accuracy of our approach. Figure 5(d) shows this accuracy as the values of these parameters change. Primarily, we observe that setting either of these values to 0 achieves low relative accuracy, showing the necessity of these regularization terms. Similarly, there is low performance when $\lambda_1 = \lambda_2 = 10$, as this causes the loss functions to be ignored. We see that the highest accuracy comes for $\lambda_1 = 0.1$, or $\lambda_1 = 1$ and $\lambda_2 = 0.1$, indicating that balancing the weight of these terms versus the loss function achieves the best performance.

V. Conclusion

Collaborative perception allows a multi-robot system to perceive an environment from multiple perspectives, which is able to use the robots that have the best views to obtain an optimal understanding of the environment. We introduce a novel approach to collaborative multi-robot perception that simultaneously incorporates view selection, feature selection, and object recognition into a unified regularized optimization formulation. Sparsity-inducing norms are designed to achieve the identification of the most representative views and features. We perform extensive evaluation on datasets, a case-study in a high-fidelity simulator, and a physical multi-robot system, with
our experimental results demonstrating both accurate object recognition as well as effective view and feature selection.

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