Heterogeneous Map Merging Using WiFi Signals

Gorkem Erinc, Benjamin Balaguer, and Stefano Carpin

IROS 2013
CSCI 9420 Paper Presentation
Fall 2013

Olimpiya Saha
12/10/2013
Outline

- Overview
- Introduction
- Related Work
- Problem Formulation
- Map Merging
- Results
- Conclusions
Overview

• Proposes a map merging algorithm capable of merging heterogeneous independent maps.

• **Heterogeneous Map Merging** - An important problem

• Relies on WiFi signals in environments.
Overview

• **Three-step** solution:

1. Overlap between heterogeneous maps being merged is determined.
2. Metric correspondences between overlapping parts are established.
3. Merging is improved

• System validated using real-life data
Outline

• Overview
• Introduction
• Related Work
• Problem Formulation
• Map Merging
• Results
• Conclusions
Introduction

• Considered the problem of merging together spatial models

• Fusing multiple heterogeneous partial models improves utility of collected information.

• Occupancy grid and Appearance-based maps

• Challenge: Spatial models lack a common representation

• Assumption: Every robot has a WiFi card

• Wireless signal strength (WSS) of all access points (APs) in range are recorded and used later.
Introduction

• Contributions:

1. Map overlap computation by **One Class Classification**
2. Development of the **first Heterogeneous Map Merging System**
3. Specification of crucial design choices
4. Evaluation and comparison
Outline

- Overview
- Introduction
- Related Work
- Problem Formulation
- Map Merging
- Results
- Conclusions
Related Work

- All previous works done with homogeneous maps.
- Map merging can be solved in **two** ways:
  1. Combination of individual models during the mapping phase
  2. Map fusion at the end of mapping process

- **Huang and Beavers, 2005**- Topological maps
- **Erinc and Carpin, 2012**- Appearance-based maps
Related Work

- Robotics-related WiFi research
  - Balaguer et al, 2012- Comprehensive survey
  - Balaguer et al, 2012 and Howard et al, 2003- Consistent WSS readings producing accurate results
Outline

• Overview
• Introduction
• Related Work
• **Problem Formulation**
• Map Merging
• Results
• Conclusions
Problem Formulation

- **Occupancy Grid Map** $M_{occ}$:
  - Environment representation as a uniformly spaced grid of binary random variables.
  - Encodes presence of obstacles at that location.

- **Appearance-based map**:
  - Undirected weighted graph $M_{app} = (V, E, w)$
  - Each vertex $u \in V$ represents an image
  - Edge $e_{ij} \in E$ connects vertices $v_i, v_j \in V$ for similar images
Problem Formulation

- Similarity measured by a similarity metric $S$
  
  $$w(e_{ij}) = S(v_i, v_j)$$

- Similarity between images defined by SIFT features

- No metric information included in Appearance-based maps.
Different types of Maps

Fig. 1: Illustrative examples for the three different types of maps presented in this paper.
Problem Formulation

- An observation acquired using a WiFi card
- $a$ denotes total number of APs in the environment
- $z^k_i$ is the WSS of the $k$-th AP measured in dBm
- $z^k_i = -100$, if the AP is invisible from a particular location.
- $Z_i$ is linked to a label $\hat{L}_i$

- **Occupancy grid maps:** $\hat{L}_i$ is represented by $C_i = [X_i, Y_i]$
- **Appearance-based map:** $\hat{L}_i$ is represented by $I_i$
Problem Formulation

- \( \hat{T} = \bigcup_{i=1}^{m} \{ \hat{L}_i, Z_i \} \) where \( m \) is the total number of observations

- \( m \) WiFi readings are partitioned into \( c \) clusters using their labels

- No clustering required for appearance based maps

- For occupancy grid maps, WiFi observations are clustered using their Cartesian coordinates.

- Most common clustering technique- k-means

\[ L = \{ L_1, L_2, \ldots, L_c \} \quad \text{with} \quad c \leq m. \]
Problem Formulation

• Clustering achieved by a modified version of **Binary Split Algorithm**
  - Algorithm combines k-means clustering with k=2 to split the data into two partitions
  - A **Stopping Condition** defined for splitting a branch in the binary tree

• **Stopping Condition:**
  - A cluster split is approved if its diameter $> d_{\text{max}}$
  - Both sub-clusters contain at least $s_{\text{min}}$ observations
Problem Formulation

• Algorithm takes \textbf{4 seconds} to cluster \textbf{1000 points}

• For each cluster, the Cartesian coordinate of its centroid is stored as a label \( L_i \) along with a vector of observations \( \tilde{Z}_i = \{Z_{i1}, Z_{i2}, \ldots, Z_{i s_i}\} \)

• \( s_i \) is the total number of observations inside cluster \( i \)

• Clusters may or may not be uniform

• \textbf{WiFi Map}: Mathematically represented as a set \( T \) of observations and their labels, \( T = \bigcup_{i=1}^{c} \{L_i, Z_i\} \).
Problem Formulation

- **Heterogeneous Map Merging Problem**: Given two maps $M_1$ and $M_2$, their corresponding WiFi maps $T_1$ and $T_2$ with the list of corresponding labels $L_1 = \{L^1_1, L^1_2, \ldots, L^1_{c_1}\}$ and $L_2 = \{L^2_1, L^2_2, \ldots, L^2_{c_2}\}$ where $c_1$ and $c_2$ are the number of clusters in $T_1$ and $T_2$, determine the mapping $f : L_2 \rightarrow \{L_1 \cup \xi\}$ where $\xi$ is the null label.
Outline

• Overview
• Introduction
• Related Work
• Problem Formulation
• Map Merging
• Results
• Conclusions
Map Merging

Fig. 2: Flowchart describing three stage of heterogeneous map merging algorithm
Map Merging

- Map merging algorithm consists of three steps:
  - Map Overlap
  - Probability Density Function Estimation
  - Regression-based PDF Refinement
    - Use edge information of appearance-based map
    - Applied regression instead of Cartesian labels
Map Merging

• Computing Map Overlap:
  - One-Class Classification Problem (OCC)
  - **Objective:** Given a set of observations in $T_1$ (i.e. the metric map) and we want to classify unknown observations inside $T_2$ to see whether or not they belong to $T_1$

• Implemented and contrasted five alternatives
Map Merging

- One-Class Support Vector Machine (OC SVM)
- Principal Component Analysis (PCA)
- K-means
- Nearest Neighbors Ratio (NN Ratio)
- Gaussian Model
Map Merging

- All OCC algorithms rely on various parameters
- **Cross-validation** of parameters performed by using a different dataset
- \( T_0 \)

- \( T_0 \) covers a large residential neighborhood (2 km)
- 200 APs

- 50% of positive test cases reserved for training

- Remaining 50% of positive and 50% negative test cases reserved for classification
Comparison Results

- **200 meters** of one floor in an office building where **48 APs** are discovered

- **20** observations recorded for each location

- Experiments ran for **50** times
Map Merging

- **Probability Density Function Estimation**
  - Labels belonging to the overlapping regions of the maps considered for merging.
  - Identified labels are matched using WiFi readings
  - Label matching presented as a classification problem where a function $f : Z_i \in T_2 \rightarrow \hat{L}_j$ is computed from data in the WiFi map $T_1$
  - Computation of $f$ achieved using **Random Forest(RF)**.
Map Merging

- **Random Forest (RF)**
  - An ensemble of decision trees built to reduce overfitting behaviors often observed in single decision trees
- **Decision Tree**: Binary tree constructed from random portion of training data
- **Matching label**: Label with most votes
- Trained an RF with 250 trees using $T_1$ in order to accurately classify WSS readings of all overlapping images
Map Merging

- RF classification also provides distribution of votes

- Probability distribution over the set of labels $P(L_j^1 = L_i^2 | Z_i)$ where $Z_i \in T_2$. 
Map Merging

- **Gaussian Mixture Model**

- Mixture weights are proportional to RF’s belief of being at location \( C_j \) given the observation \( Z_i \in T_2 \) (i.e., \( \phi(j) = P(L_j^1 | Z_i) \)).

- Value of \( \sigma \) required to be set

- Given an observation \( Z_i \), GMM maps a three-dimensional surface to the X-Y Cartesian space represented by occupancy grid map

- X-Y location proportional to the surface’s Z value

\begin{algorithm}
\caption{Construct-GMM\((Z_i \in T_2)\)}
\begin{algorithmic}[1]
\State for \( j \leftarrow 1 \) to \( c_1 \) do
\State \( \mu(j) \leftarrow C_j \)
\State \( \Sigma(j) \leftarrow \sigma^2 I \) \quad \text{// } I: \text{Identity matrix}
\State \( \phi(j) \leftarrow P(L_j^1 | Z_i) \leftarrow \text{Random-Forest-Predict}(Z_i) \)
\State return \( g_i \leftarrow \text{Build-GMM}(\mu, \Sigma, \phi) \)
\end{algorithmic}
\end{algorithm}
Map Merging

• **Edge-based Refinement**
  - For each image in the appearance-based map, a GMM is generated using RF classification.
  - Focuses only on WiFi readings
  - Edge information considered for improvement
  - Position estimate of an image can be fine-tuned using its neighbors
  - For each image $I_i$, an aggregated GMM $\tilde{g}_i$ is constructed
Map Merging

- Contribution of each neighbor is weighted with the edge’s weight
- Combination of neighbor’s GMM with the image GMM
- Resulting distribution is normalized
Map Merging

- Direct application of regression on the model emphasizes RF classification results a lot
- Does not provide **fail-safe** mechanisms for misclassifications
- Initial assumption that similar images should be localized nearby does not hold
- Nearest Neighbor Search returns the Cartesian coordinates of the $k$ most similar observations in $T_1$

Algorithm 2: Regression($\tilde{g}_i, T_1, Z_i \in T_2$)

1. $nn \leftarrow k$-NN($T_1, Z_i, k$)
2. $\hat{C}_i \leftarrow \frac{\sum_{i=1}^{k} nn_i \times PDF(\tilde{g}_i, nn_i)}{\sum_{i=1}^{k} PDF(\tilde{g}_i, nn_i)}$
3. return $\hat{C}_i$
Map Merging

• An iterative process introduced
• Process enforces local consistency among images in appearance-based map
  \[ r_{\text{max}} = \mu + 3\sigma \]
• Any two correctly localized neighbors should lie within a distance \( r_{\text{max}} \) of each other

Algorithm 3 Refinement

1: repeat
2:   for \( i \leftarrow 1 \) to \( c_2 \) do
3:     \( \hat{C}_i \leftarrow \text{Regression}(\tilde{g}_i, T_1, Z_i \in T_2) \)
4:   for \( i \leftarrow 1 \) to \( c_2 \) do
5:     for all \( I_n \in \text{Neighbors}(I_i) \) do
6:       for \( j \leftarrow 1 \) to \( c_1 \) do
7:         if \( \text{dist}(\hat{C}_j, \hat{C}_n) \geq r_{\text{max}} \) then \( \tilde{g}_i(\phi_j) = 0 \)
8:     until convergence
9: return \( \hat{C} \)
Outline

• Overview
• Introduction
• Related Work
• Problem Formulation
• Map Merging
• Results
• Conclusions
Results

• Two P3AT robots
• First robot- LMS200 laser range finder (LRF)
• Second robot- Webcam and LRF
• First floor of the Engineering building at UC Merced in 3 independent runs
• Total distance- 1 km
• Generated either an appearance-based map or an occupancy grid map
Results

- WiFi observations collection over 75 unique APs.
- Appearance-based maps composed of 234 images in average.
- In the Occupancy grid maps, over 1000 WiFi readings partitioned into 229 clusters.
- Map merging - Over 99% accuracy in average.
Results

• Each map pair merged 10 times
  
  \[ \sigma = 1.09. \]

• Average error of 90 trials is 1.21 meters with

• Overall time taken 129 seconds

• Area- 300 sq. meters

• 250 vertices and clusters

---

Fig. 4: An appearance-based map is merged with an occupancy grid map after OCC algorithm correctly estimated 100% overlap between two maps.
Results

• Fused $M_A$ with $M^1_O$ and $M^2_O$

• OC SVM is trained over each occupancy grid map

• Correct classification accuracies for $M^1_O$ and $M^2_O$ are 97.54% and 99.01% respectively

• Average accuracy of localized images - 1.06 meters

• Time - Less than 45 seconds

Fig. 5: A representative example showing an appearance-based map (left) merged with two occupancy grid maps (right) is presented.
Results

• Maps, data explored, more results and video can be found at the following link:

  • https://robotics.ucmerced.edu/Robotics/IROS2013/MapMerging
Outline

• Overview
• Introduction
• Related Work
• Problem Formulation
• Map Merging
• Results
• Conclusions
Conclusions

• Proposed the first successful Heterogeneous Map Merging System

• WiFi signals used as a common substrate

• Contemporary machine learning algorithms used to determine overlap, establish correspondences and refine the result

• Experimental evaluation with various maps

• Future incorporation of topological and feature-based maps in the system
Questions