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COMBAT ID – Combat Identification System

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14. ABSTRACT  
Integrate, test and demonstrate a fully integrated hardware and software solution running on two robot systems and three additional blue force entities. -Reliably detect blue and red force entities within a 60m radius, 180deg around each robot. -The proposed solution is designed to run through multiple classes of robot systems starting from Small UGVs through large vehicles such as trucks or tanks.

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Project scope

• Integrate, test and demonstrate a fully integrated hardware and software solution running on two robot systems and three additional blue force entities.

• Reliably detect blue and red force entities within a 60m radius, 180deg around each robot.

• The proposed solution is designed to run through multiple classes of robot systems starting from Small UGV’s through large vehicles such as trucks or tanks.
Overall System Design

Sensors
- Stereo Camera
- IMU
- GPS
- RF-Ranging

Friend-Foe Tracking
- People/Vehicle Detection
- Single Robot Friend/Foe Classification & Tracking
- Multi-Robot Friend/Foe Classification and Tracking

Navigation
- Distributed Aperture Visual Odometry
- Local Kalman Filter
- Distributed Multi-Robot Kalman Filter

External Inputs

Location Hypothesis from Other Robots

Solder Unit (RF-radio + GPS)

Robot Geo-Position

Friend & Foe Geo-Positions

GVSETS
Block Diagram

SA Capture Video → Stereo → Disparity-based Detector → Appearance classifier → Candidate ROIs → Non-Maximum Suppression → Confirmed ROIs → Friend/Foe Labeling → Labeled ROIs → Image Display

SA Capture IMU → Visual Odometry → Camera Pose → Raw data → Position Filter → Filtered data → Second robot

GPS, RF Ranging → Raw data → Position Filter → Filtered data → Second robot

Detections (Map Display) → Map Display
System installed on TALON

- Vertical Stereo Camera
- GPS Antenna
- RF Ranging Antenna
- 900MHz & 5GHz Antennae
- Processing platform
Fisheye Vertical Stereo

Top Fisheye Image

Cylindrical Mapping

Bottom Fisheye Image

Vertical Stereo

Disparity Image
(bright close, dark far)
Fisheye vertical stereo example

Stereo Reference Image

Disparity Image (closer points are brighter)
• **Accurate Person Recognition** is difficult because of low numbers of pixels on target, deformation and articulation, and shadows/glare.
• There are many modern approaches for person/pedestrian classification.
  – All of these use statistical learning methods to recognize patterns in the input.
  – However, none is perfect (less than 1 false positive per frame is “excellent” performance), because of the inherent difficulty of the task.
• We use **Hierarchical Feature Learning** to automatically learn custom features and a classifier directly from data.
• This is a fully supervised learning method, so it relies on a broad array of annotated ground truth data. We hand-labeled 25 video sequences for this purpose.
• The Learning architecture is called a Convolutional Neural Net, and is described on the next slide.
Convolutional Neural Networks (ConvNets) are one method for simultaneous feature learning and classifier training. Since they involve training multiple, stacked non-linear transforms, they are considered an architecture for Deep Learning.

**ConvNet architectural components:**

- **convolution layers**
  - extract features using small local receptive fields
  - detect patterns with increasing complexity
  - use spatial or temporal weight-sharing
  - allow complex, nonlinear transformations

- **subsampling layers**
  - pool features by local averaging
  - increase shift and scale invariance
  - reduce computational complexity
Person Classification

- **Our solution**: After comparison with other state-of-the-art methods, a Convolutional Neural Network (ConvNet) was chosen
  - Uses 2 inputs: appearance and disparity map

- **Network details**:
  - Modeled after similar architectures built for autonomous navigation (LAGR) and handwriting recognition (LeNet5)
  - 6 layer hierarchy (3 convolutional layers, 2 pooling layers, and a fully connected layer)
  - 80x40 pixel field of view with dual input layers
    - 1st layer: normalized 8bit grayscale
    - 2nd layer: normalized disparities
  - 8,000 trainable parameters.

- **Training process**: Based on human-annotated videos
  - 800,000 labeled **positives** (ROIs with vehicles) and **negatives** (ROIs with no vehicles)
  - Network parameters are optimized using stochastic gradient descent
Convolutional Neural Network Architecture for Pedestrian Classifier

- 6 layer network with dual input layers: image and disparity
- 2 outputs: person/non-person
Pedestrian: Dataset examples of image input layer
Pedestrian: Dataset examples of disparity input layer
Pedestrian Classification Results

• We have performed extensive testing of the pedestrian classifier over datasets taken throughout the year
  – Each dataset contains 4-6 collections gathered in different environments including open areas, parking lot, and forest.

• Metrics - We used standard metrics used in the literature:
  – Recall is the ratio of positive detections and *all actual positives* in the dataset. This measures how well the classifier picks up people.
  – Precision is the ratio of true positives and *all detections* returned by the classifier. This measures how specific the classifier’s detections are to people.
  – False positives per image (FPPI) is the mean number of false positives per image.
Pedestrian Classification Results

- We have performed extensive testing of the pedestrian classifier over datasets taken throughout the year
  - Each dataset contains 4-6 collections gathered in different environments including open areas, parking lot, and forest.
- Dataset: 2011.06.06: Fisheye and 80 degree
- Five sequences, both stationary and moving camera
Pedestrian Classification Results

- Metrics - We used standard metrics used in the literature:
  - Recall is the ratio of positive detections and *all actual positives* in the dataset. This measures how well the classifier picks up people.
  - False positives per image (FPPI) is the mean number of false positives per image.

![Graph](image1)

**Fisheye**

![Graph](image2)

**80 Deg**
Vehicle appearance varies widely due to viewpoint, body type, occlusion.

Our solution: A second Convolutional Neural Network (ConvNet) was trained to recognize vehicles.
  - Can learn extreme variability in object appearance
  - Fast runtime performance
  - Trained on raw data without extensive preprocessing or parameter tuning

Network details: The vehicle ConvNet is similar to the pedestrian ConvNet:
  - 6 layer hierarchy (3 convolutional layers, 2 pooling layers, and a fully connected layer)
  - 60x30 pixel field of view
  - 12,000 trainable parameters.

Training process: Based on human-annotated videos
  - 580,000 labeled positives (ROIs with vehicles) and negatives (ROIs with no vehicles)
  - Network parameters are optimized using stochastic gradient descent
Vehicle Classifier – Qualitative Results
Visual Odometry

SA Capture Video → Stereo → Disparity-based Detector → Appearance classifier → Candidate ROIs → Non-Maximum Suppression → Confirmed ROIs → Friend/Foe Labeling → Labeled ROIs

SA Capture IMU → Visual Odometry → Camera Pose → Raw data → Position Filter → Filtered data → Confirmed ROIs

GPS, RF Ranging → Raw data → Position Filter → Filtered data

Image Display

Second robot

Detections (Map Display) → Map Display
Outdoor Loop Closure Test

Top View

Side View

Visodo+IMU
Visodo
### FishEye Loop Closure Test Results

<table>
<thead>
<tr>
<th>Outdoor</th>
<th>Total Travelled Distance (meter)</th>
<th>Loop Closure Error (meter)</th>
<th>Drift Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loop 1 Visodo</td>
<td>124.9396</td>
<td>1.1138</td>
<td>0.89</td>
</tr>
<tr>
<td>Loop 1 Visodo+IMU</td>
<td>124.0460</td>
<td>1.0812</td>
<td>0.87</td>
</tr>
<tr>
<td>Loop 2 Visodo</td>
<td>122.4757</td>
<td>0.8724</td>
<td>0.71</td>
</tr>
<tr>
<td>Loop 2 Visodo+IMU</td>
<td>122.3237</td>
<td>0.7168</td>
<td>0.58</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Indoor</th>
<th>Total Travelled Distance (meter)</th>
<th>Loop Closure Error (meter)</th>
<th>Drift Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loop 1 Visodo</td>
<td>51.2833</td>
<td>0.4648</td>
<td>0.91</td>
</tr>
<tr>
<td>Loop 1 Visodo+IMU</td>
<td>51.3082</td>
<td>0.3699</td>
<td>0.72</td>
</tr>
<tr>
<td>Loop 2 Visodo</td>
<td>105.9501</td>
<td>0.5210</td>
<td>0.49</td>
</tr>
<tr>
<td>Loop 2 Visodo+IMU</td>
<td>105.9180</td>
<td>0.5015</td>
<td>0.47</td>
</tr>
</tbody>
</table>
(M_c, M_1, M_2, M_3, …M_m): m+1 mobile nodes, M_c is the central Visodo/IMU/GPS/RF node. Other nodes are GPS/RF nodes.

M_c - (X_c, Y_c, V_c^X, V_c^Y): The simplified representation from our error-state EKF
M_i - (R_i, \theta_i, V_i^X, V_i^Y, b_i): A normal EKF (no IMU, odometry) but in “relative-polar”(RP) coordinate system. The origin is the position of M_c, which can move.

Polar representation is less used in EKF, but recently has been proved to be better suited for applications such as navigation with mapping of static RF-ranging nodes.

We developed a new relative-polar formulation in EKF for our application (moving RF-ranging nodes, no odometry information).
Three Static Nodes - 2011.01.20-14.24.27

GPS Only

RP-EKF (GPS+RF-Ranging)

171
173
174
Loop closure test

<table>
<thead>
<tr>
<th></th>
<th>Loop Closure Error (meter)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visodo</td>
<td>0.2554</td>
</tr>
<tr>
<td>GPS</td>
<td>7.6335</td>
</tr>
<tr>
<td>GPS+RF</td>
<td>4.3725</td>
</tr>
</tbody>
</table>

Travelled Distance: 74.69 meters

Blue: Visual Odometry
Yellow: GPS
Green: RF + GPS
Friend/Foe Labeling

- SA Capture Video
- Stereo
- Disparity-based Detector
- Appearance classifier
- Candidate ROIs
- Non-Maximum Suppression
- Confirmed ROIs
- Labeled ROIs
- Image Display

- GPS, RF Ranging
- Visual Odometry
- Camera Pose
- Position Filter
- Filtered data
- Raw data
- Second robot

- Raw data
- Filtered data
- Position Filter
- Camera Pose
- Visual Odometry
- GPS, RF Ranging

- Map Display
- Detections (Map Display)
Association Example

ROIs & RF/GPS

* People ROIs
• RF/GPS
Image and map displays

- **SA Capture Video**
- **Stereo**
- **Disparity-based Detector**
- **Appearance classifier**
- **Candidate ROIs**
- **Non-Maximum Suppression**
- **Confirmed ROIs**
- **Friend/Foe Labeling**
- **Labeled ROIs**
- **Image Display**
- **Second robot**
- **Detections (Map Display)**
- **Map Display**

- **GPS, RF Ranging**
- **Visual Odometry**
- **Raw data**
- **Camera Pose**
- **Position Filter**
- **Filtered data**
- **Position Filter**
- **Filtered data**
Image display

Map display
- Friend 1
- Friend 2
- Foe 1
- Foe 2
- Second robot
- First robot (Camera Location)
- Friend 3 (outside camera Field of View)

Detection display
Baseline Testing

• Baseline testing for the system was performed with combination of Friends, Foes and vehicles at varying distances.
• The Friends (up to three) and Foes (up to six) were systematically tested in varying combinations moving in front of the robots at ranges from 10 to 100 meters.
• The Friends/Foes varied in speed and motion from a slow crawl to a fast sprint.
• Similar testing was then preformed with automobiles. One to three vehicles varying from parked to moving at 25 mph at ranges from 10 to 100 meters.
• The EETs then became more complicated. Introducing various sets of Friends, Foes and vehicles in random patterns to try and find the failure point of the system.
Baseline Testing

2 Friends, 1 Foe at 40m (80deg camera)
Multiple tests (Fisheye camera)

• Several tests:
  – Three friends at ~20m
  – Foes at 10, 20, 30 and 40m
  – Friends at 20 and 50m
Scenario Testing

- The first Scenario was setup with friendly forces being dug into their fighting positions with two fixed Combat Identification robots monitoring the fields of fire. The enemy could attack at any moment and the robots would have to identify if the personnel approaching the FOB were friendly forces or enemy forces before any friendly forces could engage the target.

- The second scenario was identical to the first scenario with the exception that one of the Combat Identification robots could move across the field of fires in order to establish a better line of sight to identify the targets as friendly or enemy threats.

- In the third scenario, the friendly forces conducted patrols from the FOB to a local village; upon returning from the mission the two fixed Combat Identification robots would have to identify the objects as friendly before access would be allowed into the FOB.
Scenario 1

Forward Operating Base (FOB) Defense
Conclusions

• There is a need to increase available resources by eliminating tasks that are conducted by humans and having robots complete these tasks. The Combat ID system addresses this need by allowing for a broader field of view/line of sight and object movement detection then one single person can accomplish.

• The CombatID program successfully showed that a unmanned robotic equipped with the CombatID payload could scan the same line of sight as a Soldier.

• As Soldiers and commanders become more accustomed robots on the battlefield, the acceptance and utility of CombatID like capabilities will become combat multipliers for the operational commander.