Dismount Tracking and Identification from Electro-Optical Imagery

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ABSTRACT

With the advent of new technology in wide-area motion imagery (WAMI) and full-motion video (FMV), there is a capability to exploit the imagery in conjunction with other information sources for improving confidence in detection, tracking, and identification (DTI) of dismounts. Image exploitation, along with other radar and intelligence information can aid decision support and situation awareness. Many advantages and limitations exist in dismount tracking analysis using WAMI/FMV; however, through layered management of sensing resources, there are future capabilities to explore that would increase dismount DTI accuracy, confidence, and timeliness. A layered sensing approach enables command-level strategic, operational, and tactical analysis of dismounts to combine multiple sensors and databases, to validate DTI information, as well as to enhance reporting results. In this paper, we discuss WAMI/FMV, compile a list of issues and challenges of exploiting the data for WAMI, and provide examples from recently reported results. Our aim is to provide a discussion to ensure that nominated combatants are detected, the sensed information is validated across multiple perspectives, the reported confidence values achieve positive combatant versus non- combatant detection, and the related situational awareness attributes including behavior analysis, spatial-temporal relations, and cueing are provided in a timely and reliable manner to stakeholders.

Keywords: Group Tracking, Behavior Analysis, Human, Activity-based Intelligence, Information Fusion, Identification

1. INTRODUCTION

Dismount tracking is the concept of tracking a person either by direct observation or indirectly by inference, such as determining where the person was when exiting direct view (i.e. in a car, building, or dwelling). The concept of dismount tracking is important for security in that a nominated person needs to be tracked through various activities to predict and mitigate harmful actions, establish intent, and determine social group association. Being able to conduct a behavioral analysis of dismounts requires coordination among many sensors, databases, and intelligence reports in a hierarchical or layered architecture.

Layered sensing is aimed at providing universal situational awareness with global coverage [1, 2] across traditional sensing and emerging network (i.e. cyber space) databases. A scenario of layered sensing is shown in Fig. 1 [3] wherein high altitude platforms afford target detection, unmanned aerial vehicles (UAV) maintain area surveillance for target tracking [4], and ground sensors provide individual audio reports for target identification [5]. The targets can be people, vehicles, or entities (i.e. groups of objects). Ancillary information acquired through networks can aid in the targeting such as a tracking a dismount which leaves a building in a car [6] and exits the car to go into another meeting place.

Layered sensing-derived dismount tracking incorporates many *sensors* (e.g. electro-optical/ Infrared (EO/IR) [7], radar [8]), *algorithms* for simultaneous tracking and identification, [9, 10] situational awareness (e.g. behavioral intent [11] and site security [12]), and *databases* for behavior tracking and forecasting. For successful dismount tracking, key developments necessitate use of contextual information as well as knowledge management for determining dismount activity in relation to the situation [13], user interaction with tracking algorithms to diagnose dismount suspicious (intended) but yet unobserved information [14], and understanding culture [15].

Layered sensing also includes human operators that are observing the data, making refinements [16], and providing reports based on context [17]. The user utilizes the machine tracking and identification results [18] over different scales [19] for situation awareness [20, 21]. The combination of the sensor, user, and management (SUM) [22] provides a comprehensive analysis of the data in the layered system [23].

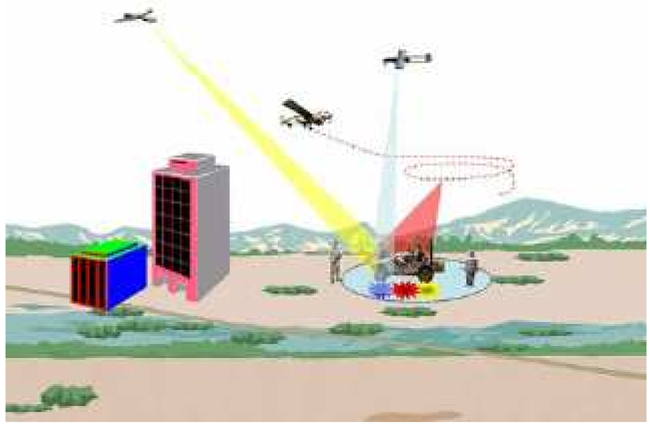

Figure 1: Layered Sensing Concept [3].

The rest of the paper is as follows: Section 2 overviews the layered sensing concept for detection and tracking. Section 3 describes dismount tracking data sets and Section 4 provides an example. Section 5 provides a comprehensive study of the operating conditions including the sensors, targets, and environments. Section 6 concludes the paper.

2. LAYERED SENSING SOLUTION

Managed layers of sensors offer capabilities to robustly track dismounts over various operating conditions of various targets, sensors, and environments. Numerous advances in algorithms, database methods, and sensors offer opportunities for future capabilities. Inherent in the analysis are three techniques: (1) feature extraction, processing, and tracking for targeting, (2) common data sets for analysis and algorithm comparison over environmental conditions, and (3) persistent wide-area motion imagery for long-term consistent sensing.

2.1 Feature Tracking and Identification (Targets)

For tracking dismounts, various features are important to determine the identification (ID), behavior, and location of the dismount. The features for ID would include the face, hair color, and size. These features would aid in tracking through occlusions, illumination changes, and links to common data bases. [24] The behavioral features are those related to the global movement, relation of body parts to the centre motion for local movements, and common attributes that aid in affiliation/association of members in group movement. The location features give the relation of the dismount to the buildings and other humans, vehicles, animals, and clutter (HVAC).

Feature processing includes various techniques and methods; which are tailored to the target of choice. For example, using imagery regions, edges, and texture support both target and background analysis. Typically, the feature information is used as likelihood values [25] (shown in Figure 2) or features can be grouped together for target recognition to enhance tracking.

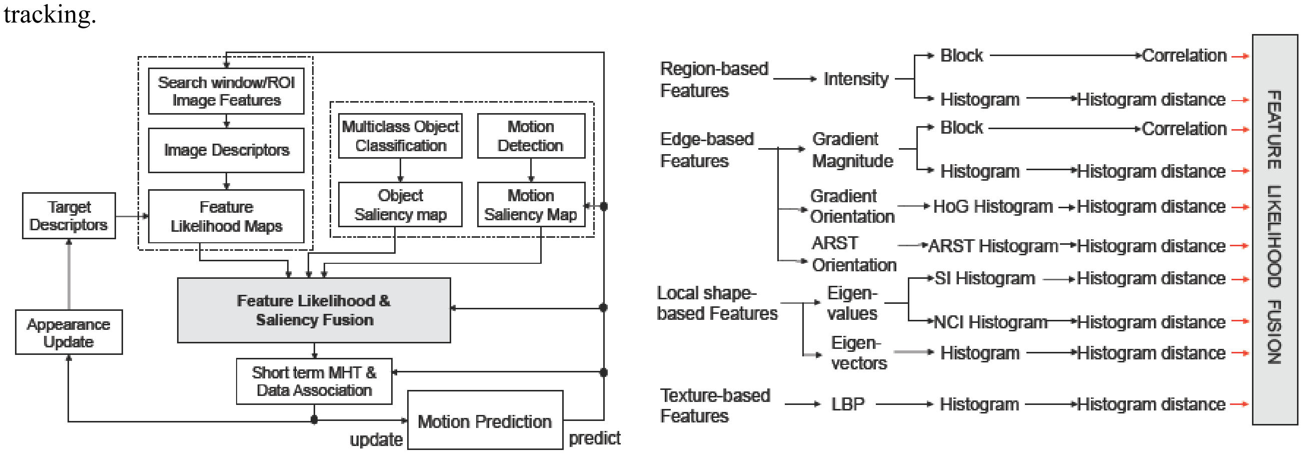

Figure 2: Feature Processing [24].

2.2. Common Datasets of Dismounts (Environment)

Table 1 contains a sampling of data sets that facilitate the developments of elements of dismount tracking .These data sets offer ground-based and overhead views for dismount detection analysis. Future data sets would come from aerial (i.e. UAVs) for detection of individuals and group activities.

Here are some data sets that support various environmental issues related to human activity research. These are found at (http://www.ecse.rpi.edu/~cvrl/zengzhi/html/ActivityRecognition/Activity_Datasets.htm) [26].

Table 1: Example Summary of Data Sets useful for Human Activity Analysis.

Data Set	Activities	Public Website
	Human Activity Analysis	
ISL-Activity	Individual Behaviors in a parking lot	http://www.ecse.rpi.edu/~cvrl/zengzhi/html/ActivityRecognition/activitydemo.htm
CAVIAR	Individual to group activities in front of buildings	http://groups.inf.ed.ac.uk/vision/CAVIAR/CAVIARDATA1/
Weizmann	Person in front of Vegetation	http://www.wisdom.weizmann.ac.il/~vision/SpaceTimeActions.html
KTH	Individual in open field	http://www.nada.kth.se/cvap/actions/
CANTATA	Numerous PETS activities PETS00-01-Outdoor people/vehicle tracking PETS02- Indoor people tracking PETS03- Face tracking in meeting PETS03-People playing outdoor soccer PETS04 – People in urban setting PETS05 - detection/tracking scenes on water PETS06- Surveillance of public spaces PETS07-Multisensor suspicious activities BEHAVE(07)–Group Actions i-LIDS(07)–Indoor/Next to building actions	http://www.hitech-projects.com/euprojects/cantata/datasets_cantata/dataset.html
	Semantic Activity Labeling	
LSCOM	Semantic extraction of activities	http://www.lscom.org/downloads.htm
SDHA	Wide area surveillance urban activity	http://cvrc.ece.utexas.edu/SDHA2010/Wide_Area_Activity.html#23Data
UCF	Sports actions from ground and aerial views	http://server.cs.ucf.edu/~vision/
	Other	
Berthold	Traffic at intersections	http://i21www.ira.uka.de/image_sequences/

From the above list, including information and links to data sets, there are also numerous publications to support the analysis and performance results. For example, in addition to compiling the data sets, in [27], Nguyen, Ji, and Smeulders use contextual information to robustly improve dismount tracking that can be used for *human activity analysis*. Another project, CAVIAR: Context Aware Vision using Image-based Active Recognition, includes a large compilation of information including overviews of data sets [28]. Focus includes features of the human body for activities [29] that support human actions [30]. As listed in Table 1, the Performance Evaluation of Tracking and Surveillance (PETS) community has numerous data sets, challenge problems, and performance analysis results [31].

Another area of research includes *semantic labeling* of human actions in the Large Scale Concept Ontology For Multimedia (LSCOM) project [32]. In LSCOM, not only are actions labeled, but semantic information is used to rank video shots according to the presence of semantic concepts (e.g., "sports", "people marching", etc.). Other examples include the Semantic Description of Human Activities (SDHA) [33] program and detection of sports activities from different views [34] in which the semantic labeling is understood from the context. New sensors enabling persistent wide-area imagery for layered sensing can extend the human activity analysis as well as semantic labeling of behaviors over extended spatial and temporal coverage.

2.3 Wide Area Motion Imagery (Sensors)

Wide Area Motion Imagery (WAMI) is an emerging capability that affords large spatial coverage, constant monitoring over time, and potential for diverse frequency sensing (e.g. EO/Radar). Since the WAMI data covers a city (Figure 3), the ability to maintain track (after initiation) is increased as the object is within the sensed region of interest for potentially an extended duration. [2]. Likewise, with constant staring, there is the increased advantage of extending track lifetime by linking associated tracks, projecting tracks onto road networks [35], recovering from lost tracks, and coordinating hand-off to ground sensors. Finally, with the advent of WAMI, there are other modalities emerging for electro-optical visual cameras, moving synthetic aperture radar (SAR), and hyperspectral (HSI) methods. Together, these sensors provide a rich new set of data that needs to be exploited for dismount analysis in addition to the traditional vehicle tracking.

WAMI data provides new opportunities that relate to targets and environments, increasingly so when combined with other sensors such as ground-based detectors. WAMI data sets cover a broad range of environmental conditions and various target behaviours as listed above. Using the organized data sets for dismount tracking algorithm development, the basic techniques such as tracking and behavioural semantic labels can be applied over a larger spatial and temporal setting. As an example, in the Columbus Large Image Format (CLIF) data set [2], identified conditions include sensor system performance (camera motion and frame rate, contrast, and camera model fidelity), targets (turning, type, and speed), and environments (shade, occlusion, on and off roads).

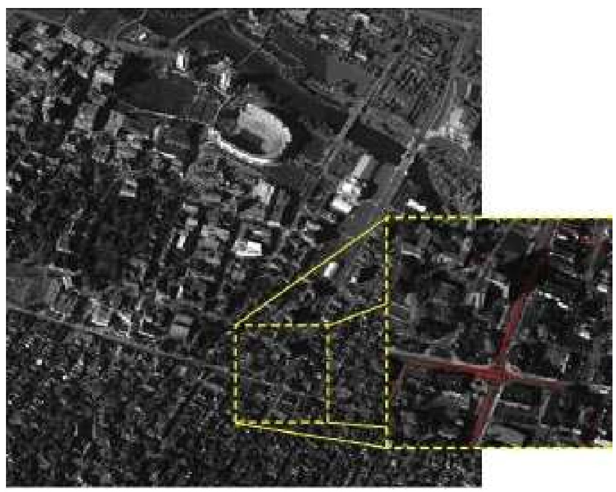

Figure 3: Wide Area Motion Imagery (WAMI) [2].

3. LAYERED SENSING DISMOUNT TRACKING DIRECTIONS

With layered sensing, there are new possibilities for advanced capabilities that require further analysis. Future directions would leverage recent techniques across the emerging "wide area" sensing modalities. Some areas of interest as a few highlights are categorized as sensors, targets, environments, and performance modelling. The list only compiles the most recent work from the Information Fusion Community (www.isif.org) of which other information can be gathered from other research communities.

Sensors: New developments for radar [36] include different bands and waveforms to aid in detection of activities. Hyperspectral sensing [37] affords wide-area coverage from traditional satellite imagery to enhance features, reduce correlated errors, and increase correlated detections. For example, LADAR can enhance occlusion models.

Targets: Developments include situational awareness [38] shown in Figure 4, group tracking [39, 40, 41, 42] shown in Figure 5 [43], and linking spatial locations to social network coordination of group activities [44]. A target tracking system [45] of objects includes target identity (allegiance) [46], intent [47], and vehicles of use [48]. Additionally, modeling the dismount requires a threat analysis [49] and emotion state of the players [50]. Targets also need signature analysis [51] for detecting move-stop-move patterns [52], distributed tracking techniques [53], and advanced WAMI analysis [54]. Tracking multiple dismounts [55, 56] requires real-time solutions [57] for small group activity recognition [58].

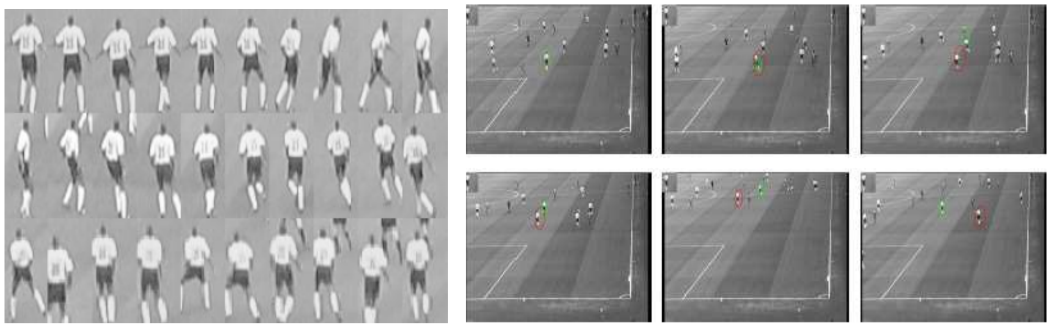

Figure 4: People Tracking over PETS data [41].

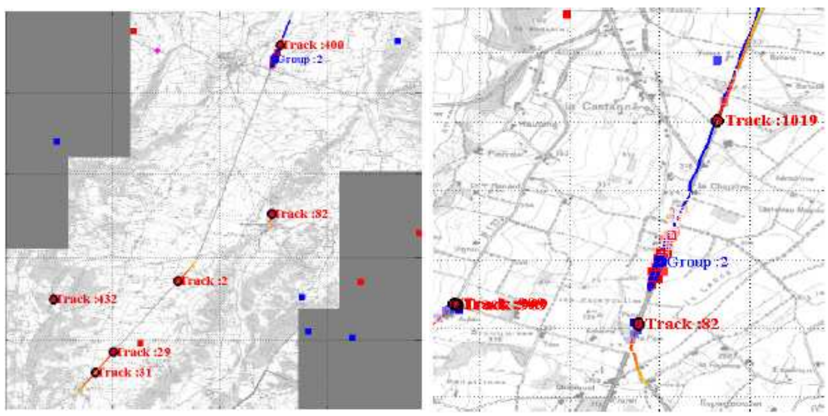

Figure 5: Group Tracking [43].

Environment: Recent developments in information fusion technology can aid in the analysis of warnings. These include (a) persistent aerial surveillance, (b) high resolution digitized terrain and weather information, and (c) increased database access support to users. Issues for further enhancement include terrain modeling (e.g., of roads and off-road paths), effects of foliage (e.g. shade occlusions from trees), and illumination changes [59]. The use of road information can aid in the track estimates of the targets. [60, 61] Collections over different times of the year introduce weather and illumination variations.

Performance Analysis: Developing analytical feature-aided tracking performance models [62] and tracking metrics [63] across the various tracking methods support sensor exploitation and can/should drive future sensor performance requirements. The performance models, with their given fidelity [64], can come from inductive analysis and be combined with deductive experimental analysis. Together, the models developed would help in feature aggregation for detection and identity, enable pattern matching approaches for both targets and behaviors, and provide predictive models for tracking though variations in sensors, targets, and environments.

The visualization of tracking dismount identities can be a 3-dimensional receiver operating characteristic (ROC) curve over time [65] from which a fusion gain can be determined [66] and displayed as a real-ROC [67]. Future performance evaluation requires situation analysis [68] that leads to analysis of both measures of performance and effectiveness [69].

4. MULTISENSOR DISMOUNT TRACKING EXMAPLE

In our example, we demonstrate dismount tracking over two sensor modalities collected from the IEEE OTCBVS WS Series Bench Color-Thermal data set from OSU [http://www.cse.ohio-state.edu/otcbvs-bench/] [70]. Figure 6 shows the dismount detection, tracking, and identification (DTI) of people using multimodal EO/IR information [71].

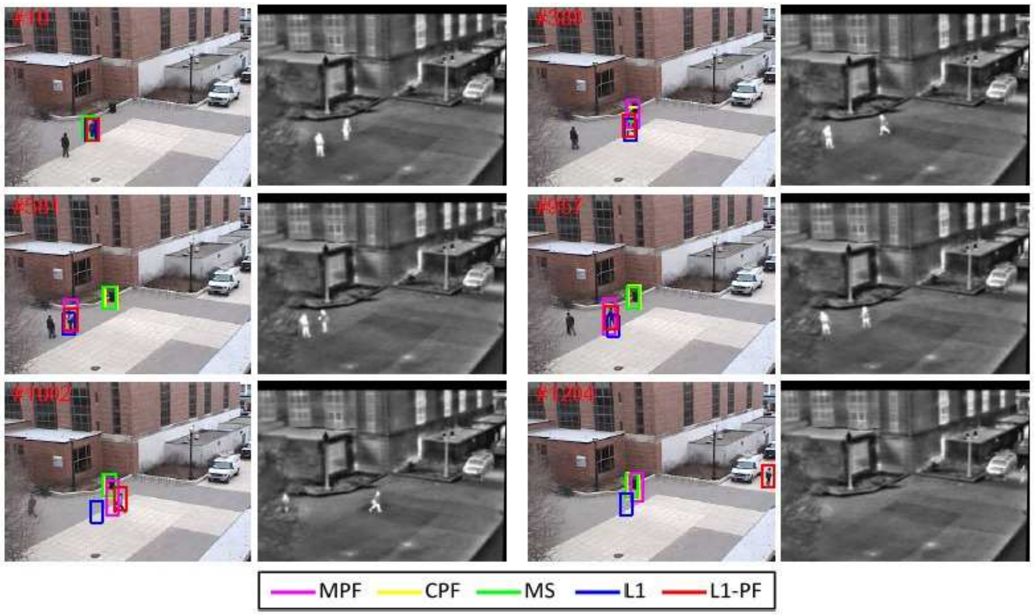

Figure 6: Dismount Tracking Example 1. **[**71**]**

Comparison of state-of-the-art visual trackers, namely, Manifold-based Particle Filtering tracker (MPF), Color-based Particle Filtering tracker (CPF), and Mean-Shift tracker (MS), the original ℓ_1 sparse representation based tracker without data fusion (L1), and the multisensor ℓ_1 sparse representation particle filter with multimodal information (etc. color edges or infrared images) (L1-PF).

In Example 1, the target activity is a person walking who stops to talk to someone else, and then continues walking until out the view of the camera. As illustrated in Figure 7, *MS* and *CPF* are attracted to the black trash can in #388 and lose the target. From image #1002, *L1* and *MPF* drift and eventually lose the target. Since the multisensor ℓ_1 sparse representation particle filter (mL1-PF) fuses the intensity with infrared information, it robustly tracks the target throughout the dismount activity changes.

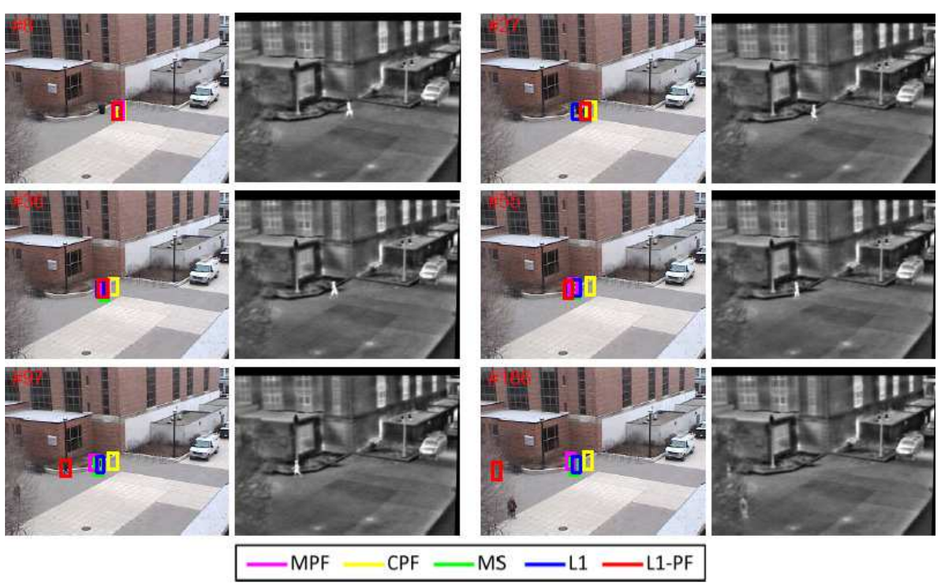

Figure 7: Dismount Tracking Example 1. **[**71]
(See Figure 6 caption for tracker types)

In Example 2, the dismount is passing near a trash can with similar color and then occluded by the branches of a tree. From Figure 7, The CPF loses the target first (#27) and then all the other compared trackers are attracted by the can and lose the target after #55. At the end of the sequence, the dismount is occluded by a tree and it is very difficult to identify it only from the intensity information. However, the infrared (IR) information tells us useful information and the *mL1-PF* approach can effectively fuse the IR data with the intensity information, of which the *mL1-PF* follows the target throughout the sequence.

In addition, using the layered sensing information from the environment and various combinations of sensors, a vast amount of targets of interest can be tracked over different dismount activities. Typical targets include vehicles, people, and crowds; however, there is a host of information in databases that could be used to augment the determination of other dismount characteristics of behavioral intent such as that used over the PETS datasets [72].

5. LAYERED SENSING DISMOUNT TRACKING ISSUES

Layered sensing provides some advantages while introducing some limitations that need to be addressed for robust dismount tracking. We summarize the main ideas in Table 2.

5.1 Advantages

Key elements of layered sensing can increase the detection, identification, and tracking of dismounts. Using Wide Area motion imagery (WAMI) can enable scene understanding and contextual analysis, aid cueing between aerial and ground sensors for tracking of human activities, determine group associations through extended spatial coverage, and increase the track lifetime of nominated dismounts (e.g. track over motion in and out of buildings, vehicles, and meetings). Extended relations and behaviors (e.g. intent) can be gathered from intelligence databases, social networks, and communication transactions that can aid the management of sensor collections, data exploitation, and cueing of other sensors.

5.2 Limitations

Layered sensing describes a general concept that incorporates many sensors, many platforms [73], over numerous target types, in diverse environments. The complexity also brings with it many limitations that need to be explored in a cost/benefit analysis. For example, overhead aerial imagery increases spatial coverage but limits the pixel resolution for feature analysis to identify dismounts. The increased number of potential targets, over dense and complex behaviors, requires sophisticated analysis of dismount group associations to reduce the display annotations of targets of interest presented to the analysts. Tracking dismounts in the real world would necessitate an understanding of how to use weather, terrain, and urban structures which temporally vary over decreasing variations; respectively.

The use of a centralized reporting of weather and terrain information would aid in dismount analysis since impending threats from weather, explosive attacks, and terrorist groups would be localized *spatially*. The ability to monitor activities persistently would account for the *temporal* aspects of events. To maintain the database of information, a third type of information could be provided to aid in dismount analysis such as *spectrum frequency* variations of data collected over various sensors.

6. DISCUSSION AND CONCLUSIONS

Dismount tracking requires pragmatic assessment of the context, culture, and situations [74, 75]. With the advent of current information fusion technology, there is a need to augment tools with information to support timely and actionable decisions [76]. This paper makes the claim that "layered sensing" supports dismount analysis through the supporting sensing technology of wide-area motion imagery over the operating conditions of the environment (terrain and weather), layered sensors (satellites, UAVs, and ground sensors) over various spectrums (electro-optical to radar), and targets (*hard*: people to *soft*: text-based group associations). Together the combined use of multi-perspective sensor data to support decision-quality information, including a standardized uncertainty ontology [77], would aid dismount detection, identification, and tracking for combatant assessment. Emerging trends require:

(1) Layered sensing of environmental data to support dismount analysis in an urban area;
(2) Layered sensing of sensor data by traditional (i.e. EO data) with newer WAMI capabilities;
(3) Layered sensing of targets (people/vehicles) by way of common and inter-operable reporting; and
(4) Layered sensing through a common database from which users can access the information.

Table 2: Issues for Layered Sensing to Support Dismount Tracking

Concept	Advantage	Limitation
	Sensors	
WAMI	Wide area scene understanding	Increased computations requiring increased ground station footprint or communications bandwidth
Multimodal	Can combine HSI, radar, and EO	Inconsistent georegistration of multiple mixed resolution sensors hinders real-time data analysis
Ground sensors	Ability to get high-resolution pixels for ID	Accuracy of reported information as well as projection of change appearance
	Targets	
Dismounts	Can track through various dynamic changes (e.g. going from car to building)	Prediction of movement through occlusions and outside-to-inside transitions
Tracking	Increased track lifetime from extended spatial coverage	Increased number of confuser objects that require rudimentary location updates
Group Association	Maintain database of dismounts associations Determine associations from the unobservable (people entering a building separately may imply association)	Separating activities of interest from routine activities Determining the intent of various groups that have yet to be identified or actions which are routine versus lead to harmful activity
Intent	Can link person to a priori known places of activity to help in tracking	Determining the unknown actions resulting from spatial activity
	Environment	
Urban	Context aiding (e.g., terrain and buildings)	High population traffic density areas; terrain masking line of sight, and construction changes
Weather	With different modalities, have the opportunity for distance and weather invariant observations.	Some sensors need to detect the variations in features due to changes in weather (e.g. illumination)
Terrain	Can observe through varying conditions (e.g. occlusions, obscuration)	Need to detect on the fly as conditions change; Linking indoor and outdoor cueing
	Use	
Analysts	Provide information to analysts	Cueing of information to many users on the ground
Social Networks	Link to available WWW for social networks	Determining the associations from textual information over various website portals
Database	Determine activities from database (e.g. credit card transactions, police records, vehicle registration records, etc.)	Delay of information to support tracking needs, including time latency and low confidence correlations
Sensor Management	Increased correlation of features for tracking and performance models	On-the-fly development of models for changing targets; high demand for limited assets

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