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Collaborative Body Sensor Networks & Multi-user activity recognition

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Outline

- **Human Activity Recognition**
  - **SPINE Body of Knowledge**

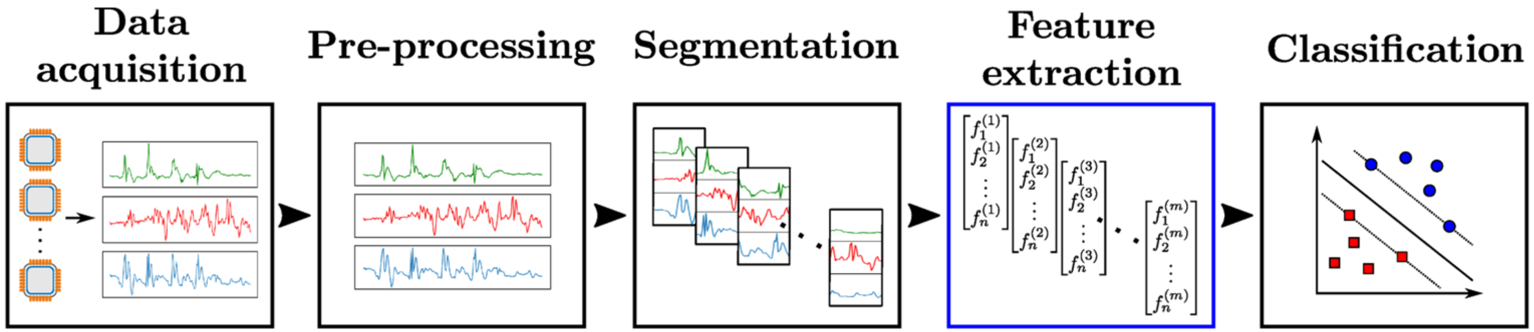
- **Collaborative Body Sensor Networks**
  - C-SPINE
  - BodyEdge

- **Multi-user activity recognition**
  - **Definitions** and categorization
  - Application **Domains**
  - **Sensing** approaches
  - **Recognition** methods
  - Research **challenges**

Human Activity Recognition (HAR)

- HAR has become a **hot research topic** in the last couple of decades thanks to availability of body-worn sensors, wearable computing systems, live data streaming and advancement in computer vision, machine learning, artificial intelligence, and IoT
- Broad field of study concerned with **automatic identification of specific movements or actions** based on sensor data.
- Movements can be common **daily life activities** performed, such as walking, talking, standing, and sitting or **more focused actions** such as those performed in a specific sport, in the kitchen or on a factory floor.
- **Sensor data** may be **recorded remotely** (video, radar, or other wireless methods) or **directly on the subject** (wearable devices or smartphones).
- Main questions:
  - "**What** action?" (i.e. the recognition problem)
  - "**Where**?" (i.e. the context problem)
  - "**Who**?" (i.e. the identification problem)

- **Basic activities**, such as "walking" and "running" arise very naturally in daily life and are relatively easy to recognize.
- **Complex activities**, such as "peeling an apple," are more difficult to identify.
  - Complex activities may be decomposed into sequence of simpler activities that are easier to recognize.

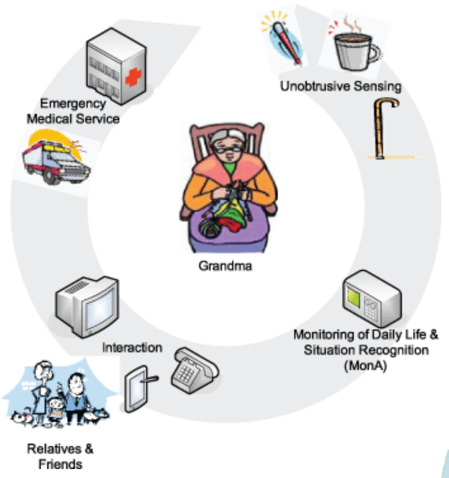


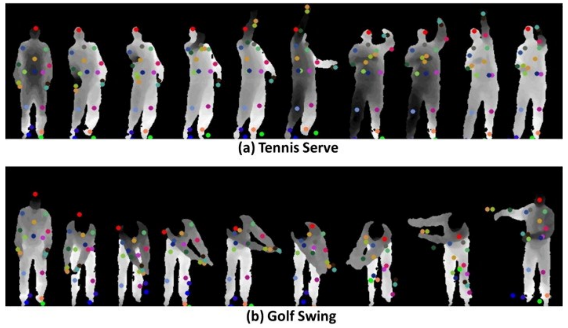
Human Activity Recognition (HAR)

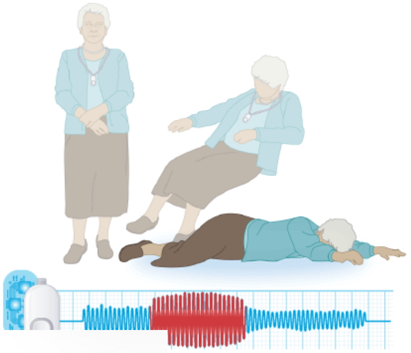
- So far, research on Activity Recognition (AR) mostly **focused on monitoring single individuals**
- For more than a decade, the problem of recognizing human actions and behavior has been addressed with **computer vision techniques**, not always with convergent results especially in unconstrained real-world scenarios
- HAR becomes **exceptionally complex in multi-user scenarios** and the literature is still in early stage
  - Given the more significant relevance of context-awareness, IoT represents a critical technological enabling factor

Domains

- Assisted Living
- Fall detection
- Sport
- Wellness
- Emergency response
- Workplace Safety
- Public security
- Sociality







SPINE Body of Knowledge

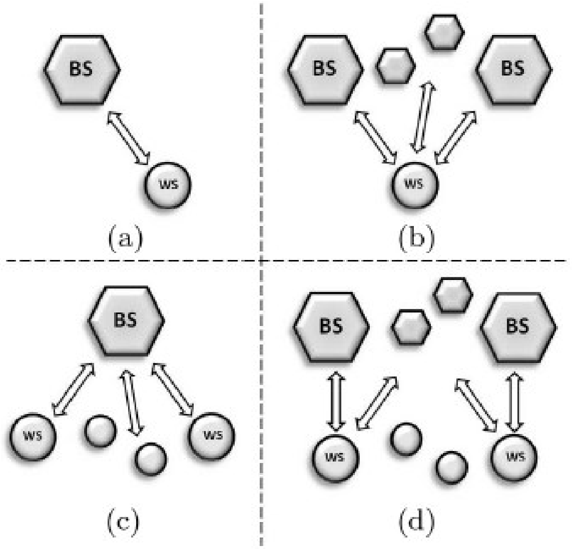
- The **SPINE Body of Knowledge** (SPINE-BoK) has over **15 years history** gemmed in the context of the **open-source SPINE project**, and includes models, methods, algorithms, frameworks, tools and systems for the **systematic and full-fledged development of wearable computing systems based on body sensor networks**.
- The SPINE project was **originally established in 2006** at the Telecom Italia/Pirelli Wireless Sensor Networks Lab in Berkeley (CA). The founders were University of Calabria, Telecom Italia/Pirelli WSN Lab, Telecom Italia Lab, and University of Berkeley.
- Since 2013, the project is **fully driven and managed by our research group at University of Calabria**.
- The **SPINE BoK includes**: the SPINE framework and related methodology, extension frameworks (SPINE2, C-SPINE, A-SPINE, SPINE-*), BodyCloud and BodyEdge infrastructures, and a rich set of application-specific multi-sensor data fusion algorithms.
- Overall, the SPINE research and **dissemination activities produced 100+ papers**, **40+ in top-level journals**, **5000+ citations**, and **5 highly cited WoS papers**.

- The **SPINE reference paper** *G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, R. Jafari: Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications. IEEE Trans. Hum. Mach. Syst. 43(1): 115-133 (2013)* received the **A. P. Sage Best SMC Transactions Paper Award 2014**.
- Our **book** includes the overall SPINE BoK contents: *G. Fortino, R. Gravina, S. Galzarano. Wearable Computing: From Modeling to Implementation of Wearable Systems based on Body Sensor Networks. Wiley-IEEE Press, 2018.*
- Learn more on our **Website**: http://projects.dimes.unical.it/spine-bok

Collaborative
Body Sensor Networks

Collaborative Body Sensor Networks

- Collaborative Body Sensor Networks (CBSNs) are wireless BSNs able to **cooperate** to achieve a **shared goal**.
- Cooperation is based on **interaction** and **synchronization** among the CBSNs and distributed computation across the interacting CBSNs
- In particular, the interaction can be activated when CBSNs are in **proximity** and based on service-specific protocols that allow for service management between the involved CBSNs.



CBSNs enable new smart wearable computing systems in the context of physical pervasive computing environments

- Different interaction models:
  - **one-to-one**
  - **many-to-one**
  - **many-to-many**

Reference paper:
Giancarlo Fortino, Stefano Galzarano, Raffaele Gravina, Wenfeng Li: A framework for collaborative computing and multi-sensor data fusion in body sensor networks. Information Fusion 22: 50-70 (2015)

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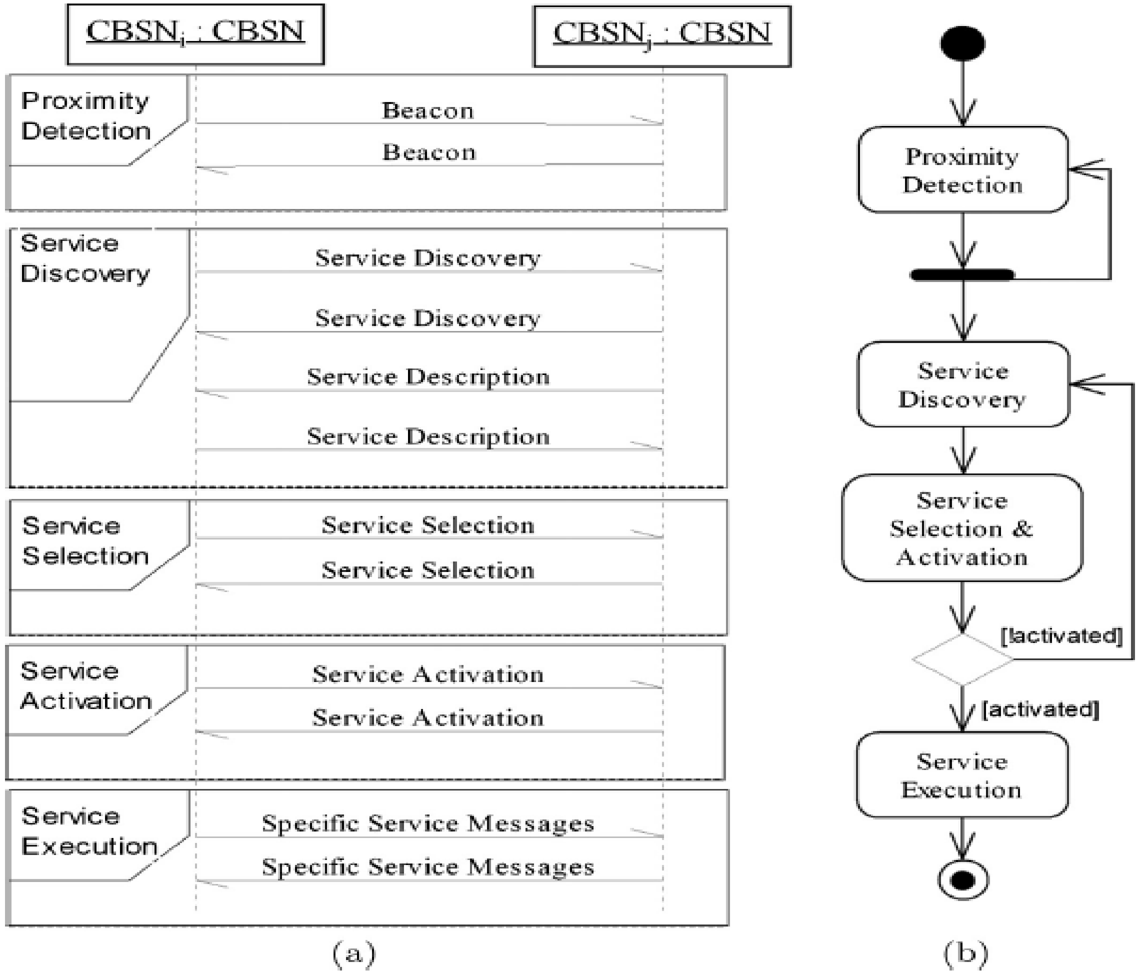
Collaborative BSNs: interaction model



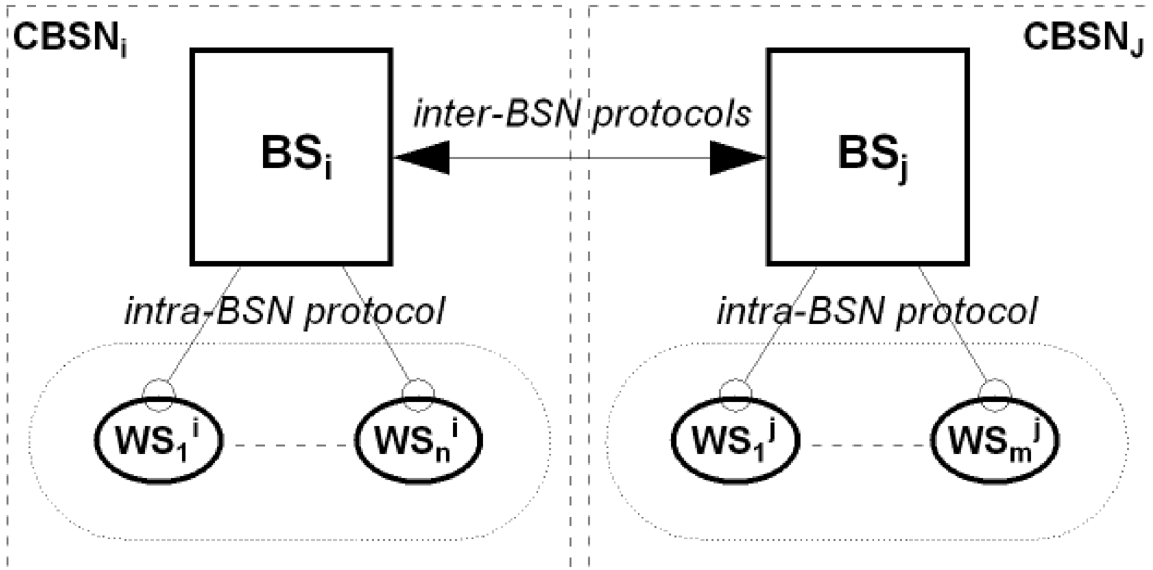
CBSN interaction and activity: (a) sequence diagram of high-level interaction among CBSNs; (b) activity diagram of basic CBSN tasks.

C-SPINE

- C-SPINE is designed around the CBSN architecture and provides basic and extensible services to **develop innovative CBSN-based applications**.

- The reference architecture of CBSN consists of two parts:
  1. the network architecture;
  2. the software architecture.

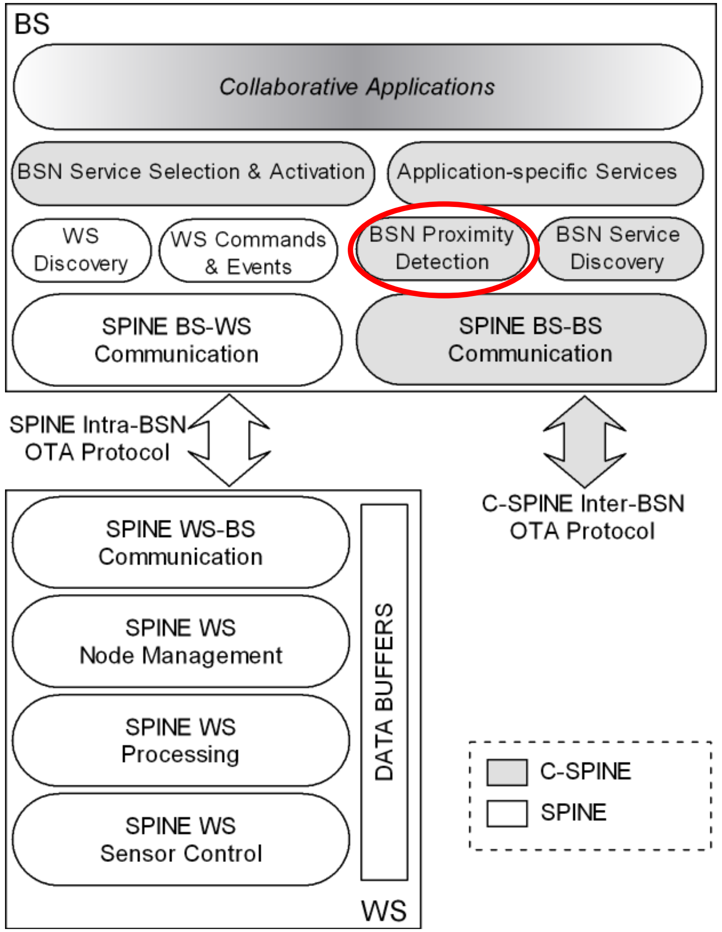
- C-SPINE is an extension of the SPINE open source Framework and part of the **SPINE Body of Knowledge**



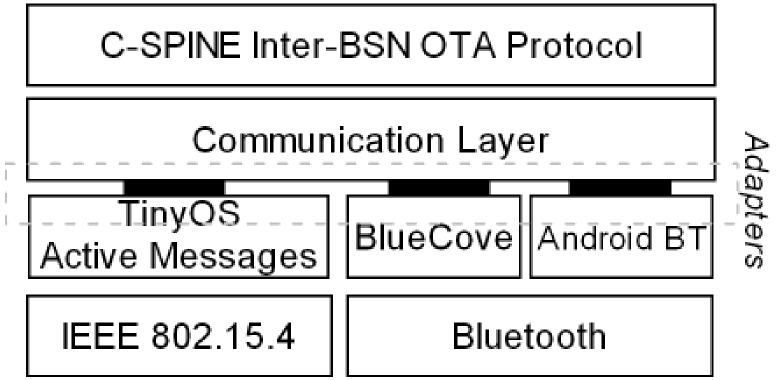
Reference paper:
Giancarlo Fortino, Stefano Galzarano, Raffaele Gravina, Wenfeng Li: A framework for collaborative computing and multi-sensor data fusion in body sensor networks. Information Fusion 22: 50-70 (2015)

C-SPINE

C-SPINE High-Level Architecture



C-SPINE Communication Layer



Multi-user and Group Activity Recognition

Definitions

ACTIVITY ≠ BEHAVIOR

- Human **activity** is an **intentional**, conscious, and **subjectively meaningful sequence of actions**
- Human **behavior** is the response of individuals or group of people to internal and external stimuli
- **Emergence** occurs when an entity has properties (or shows behavior) its parts don't have on their own
  - (**Emergent activity**) Group activity or behavior can emerge in a wider whole when the individual members interact

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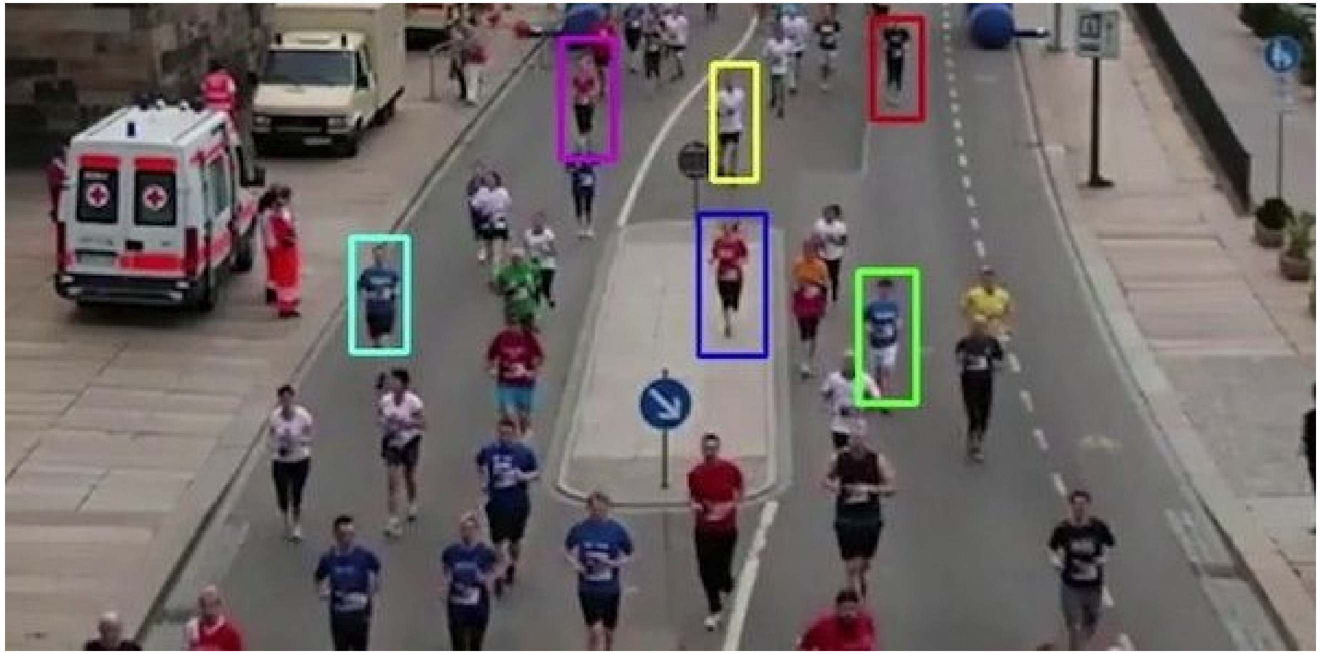
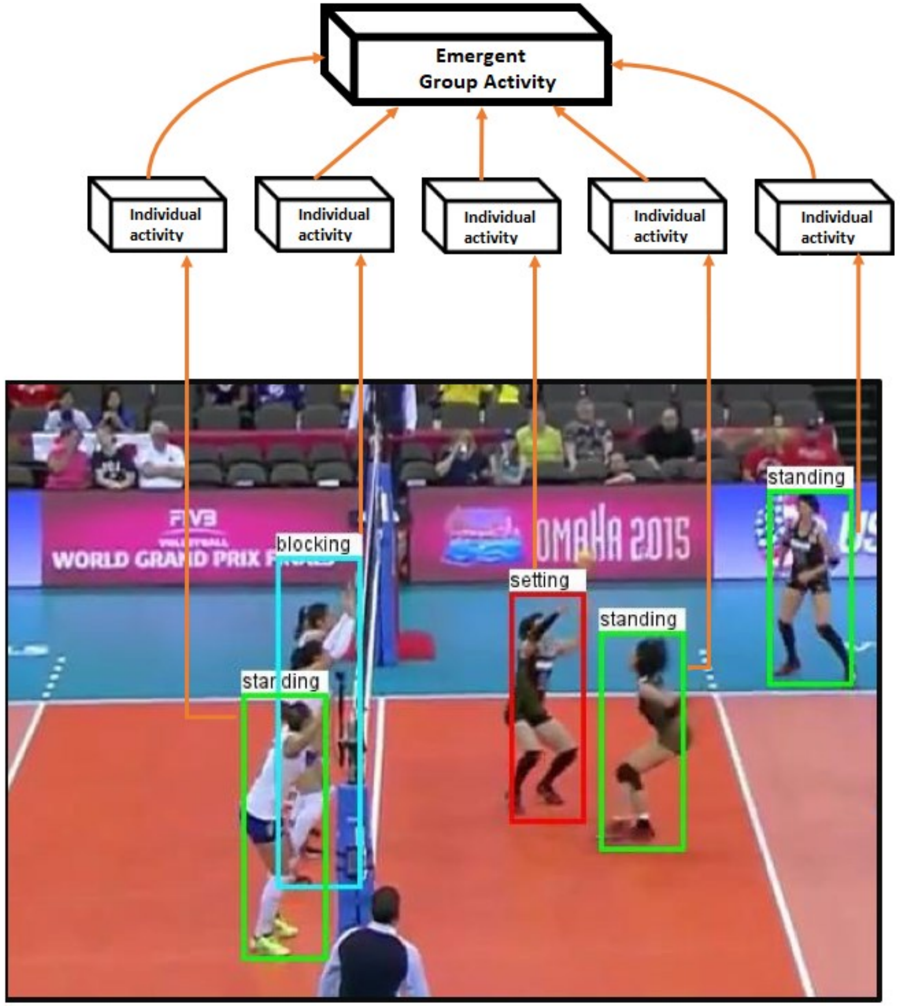
Individual *vs* emergent activity





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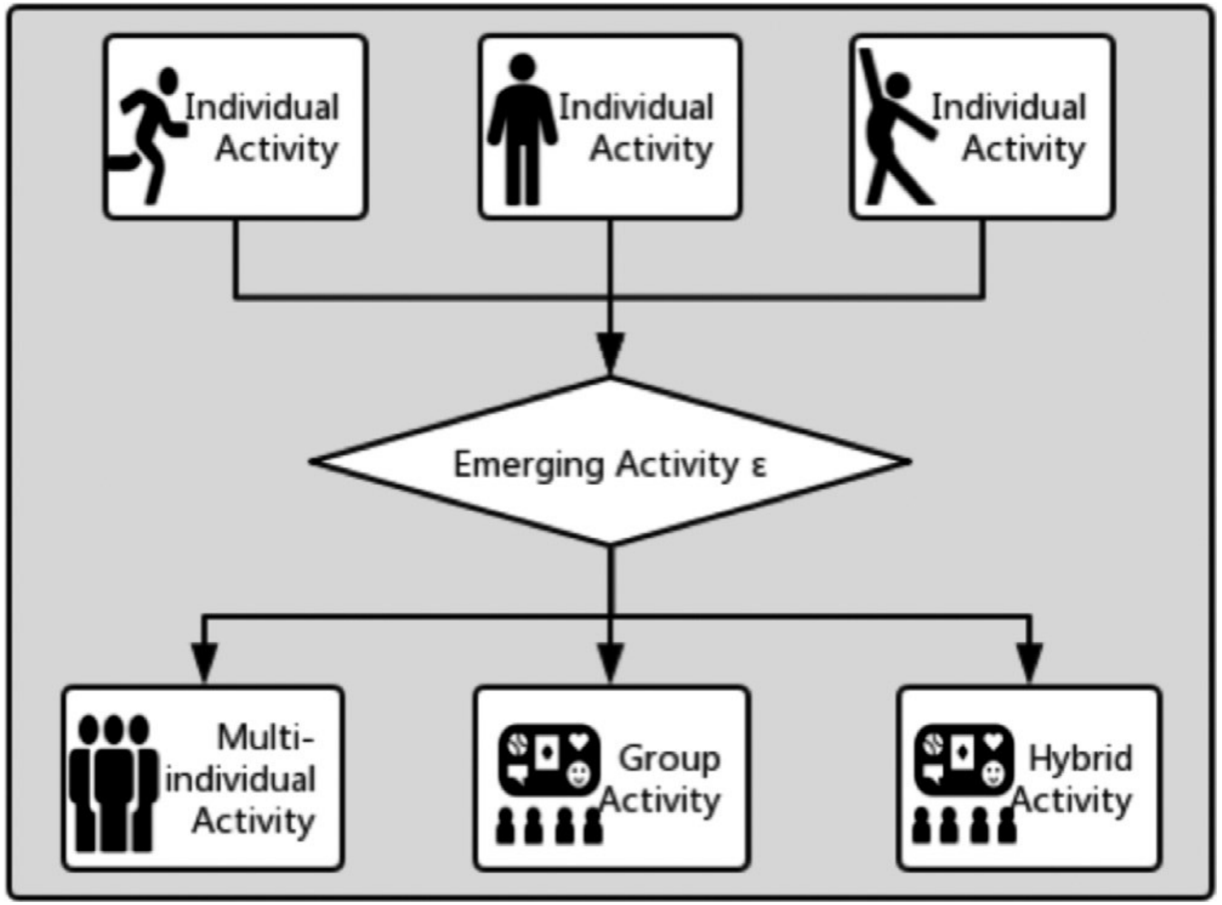
Definitions

- **Multi-user activity (MAR)** can be divided into two scenarios:
  1. multiple users (in the same environment) performing activities **individually**;
  2. multiple users interacting and physically **collaborating** performing activities to achieve a shared goal.

- ***Group activity*** - Two or more subjects have a **common goal**, which can be reached only **with a joint, coordinated activity** (e.g. lifting a heavy object from the ground which requires the collaboration of two people).
- ***Multi-individual activity*** - Two or more subjects in a given environment perform **individual activities which loosely depends on others**
- ***Hybrid activity*** - Both individual and group activities are taking place in the same “scene” (e.g. in a kitchen two people are cooking while a third one is eating seated at the table)



Qimeng Li, Raffaele Gravina, Ye Li, Saeed H. Alsamhi, Fangmin Sun, Giancarlo Fortino, "Multi-user Activity Recognition: Challenges and Opportunities", Information Fusion, 2020

Complex activities

Research Objective	Activity Type	Description
Concurrent Activity	Single-user	where a single user performs two or more activities simultaneously.
Interleaved Activity	Single-user	actions can be interleaved in multiple activities, i.e., a single user switches back and forth between two or more activities; some activities can share some actions.
Simultaneous/Parallel Activity	Multi-individual	multiple users perform same activities independently.
Conflicting Activity	Multi-individual	multiple users perform different activities independently and aim for different, conflicting goals.
Sequential Activity	Single-user/Group	actions are performed one after another.
Cooperative Activity	Group	users perform actions in support of each other's goals rather than a shared goal.
Collaborative Activity	Group	users work together and perform certain steps/actions of the activity to achieve the common goal.

- When there are multiple subjects in the environment and the relationships among them increase, the complexity level increases accordingly.

Applications of MAR

Surveillance and security

Crowd monitoring supports public security e.g. excessive crowded transports, crime scene detection, large-scale emergency management in the escape from danger (e.g. group members suddenly running in different directions can be a pre-alarm factor of public safety threat events)

An interesting work* studied the impact of individual agents' characteristics in groups evaluating the evacuation efficiency as a result of local interaction.

Tracking and localization

Technologies for tracking and localization have undergone remarkable growth for interacting multi-user scenarios in recent years, e.g. to predict human behaviors and interactions in a crowd

Smart and cognitive buildings

1. Group activity such as meetings, learning, teaching, discussions, seminar forums, influence the energy consumption of a building.
2. group behavior and context are fundamentally different from those of the individuals, so smart environments must also be aware of group activities to perform cognitive services

* A. Braun et al., Modeling individual behaviors in crowd simulation, 11th IEEE International Workshop on Program Comprehension, IEEE, 2003, pp. 143–148

Applications

Group identification and detection

Different types of groups often have different behaviors that can be detected to identify groups and recognize group membership.

Individual activities, relative velocity and proximity information are often used to determine group affiliation

Sports activity recognition

Deep Learning (DL) and sensor fusion is being applied to classify sport activity in team games such as football, beach volley, ice hockey.

Context-awareness

whether a mobile phone should ring depends on the situation, for example when having lunch or meeting. Devices must therefore be aware of our situations and contexts to behave correctly without requiring explicit input from the user

Affective computing and social analysis

monitoring eating and other activities to measure how much time a family spend together. Consequently, the level of family happiness/unity would be feasible to be estimated.

Monitoring eating together can also be an aspect of social health and wellbeing of people.

Applications

Adaptable privacy policy

Recognizing group affiliations would allow applications to provide automated support, such as sharing or tagging. However, the privacy preferences of the group are highly affected by the context and activity of the group.

Group Policies

Automatically apply group policies and permissions to users of the group and disable user account when he/she leaves the group.

Social networking

A single user can share the emergent group activity without necessarily disclosing the identity of other members, and even without knowing or requiring their identity at all.

Collaborative Education

Technology has greatly facilitated the transition from a traditional lecture-style teaching environment in which the teacher had the central role in educational activities and student were merely listener, to a knowledge-centered environment in which students are the main actors and share their process of learning

- Educational games (a.k.a. **serious gaming**) are an example *

* Musheer et al., Multiuser Simulation-Based Virtual Environment for Teaching Computer Networking Concepts, Int.nl J. on Advances in Intelligent Systems, vol 5, 2012

Sensing methods





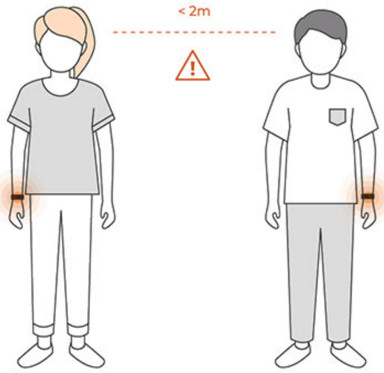
Approach	Technology	Advantages	Disadvantages
Radio	ZigBee, Bluetooth, WiFi, RFID	Low cost, contact-less	Low accuracy, environmental interference
Computer vision	Camera	High accuracy	High cost, complex computation, privacy issue, high computation demanding
Sensor	Inertial sensors, motion detectors, contact switches, break-beam sensors, pressure mats	Low cost	Low accuracy
Hybrid	mixed by above sensors	High accuracy	High cost (with camera), complex computation, privacy issue (with camera), difficult to fuse information

Sensing methods: *radio-based*

- **Bluetooth**

  to detect the group affiliation using proximity feature via RSSI.

  However, it cannot be used for fine-grained localization and only provides range information without direction.

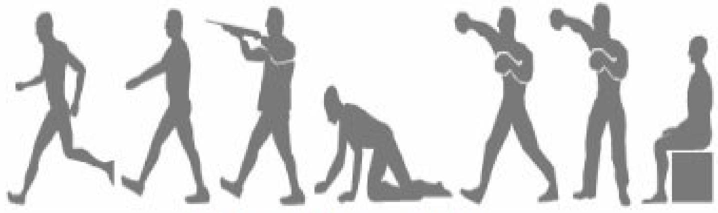


- **Channel State Information (CSI)**

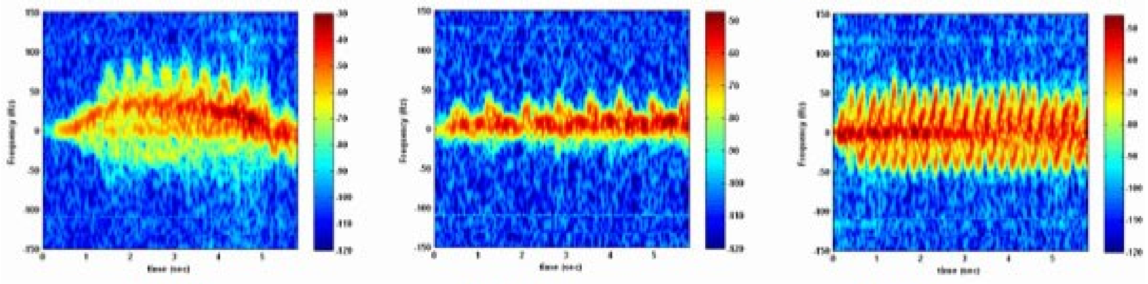
  To measure channel properties (e.g., scattering, fading, and power decay with distance) of a communication link.

  It is used in fine-grained device-free motion detection and in-door localization

<Doppler radar>



<Different human activities>



<Running> <Crawling> <Boxing>

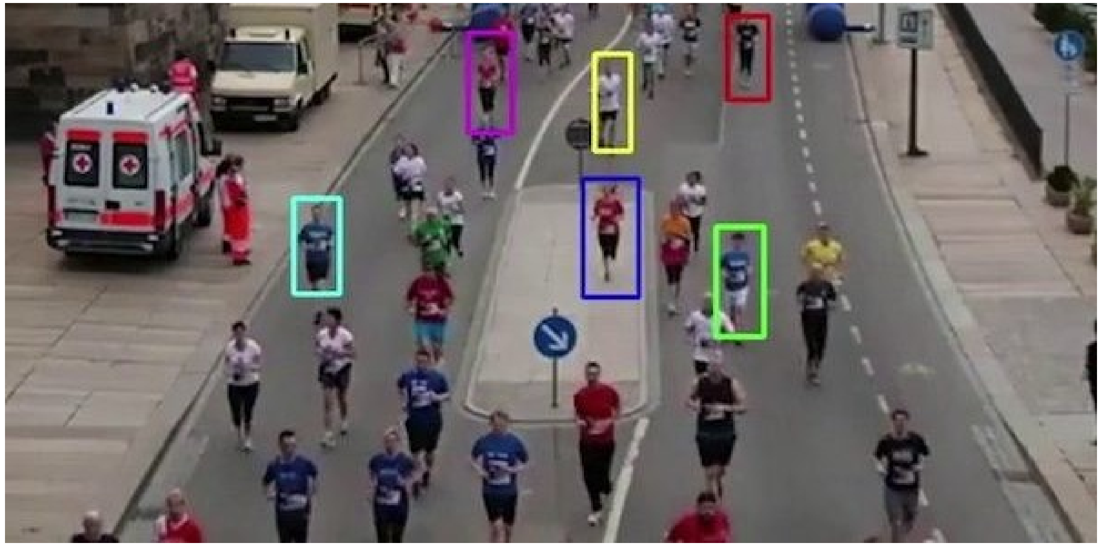
- **UWB Radar**

Sensing methods: *vision-based*

- Computer-vision based is used for abnormal group behavior detection, video surveillance, public security.

- It allows to **captures the activity of each individual** in the scene and the **interactions among individuals** to recognize group activities.

- **Background information is important** to improve recognition accuracy.
- Hierarchical-based models often adopted to **consider scene, action, and poses** to recognize group activity.
- **Fusion of person-level and scene-level features** improves MAR prediction.



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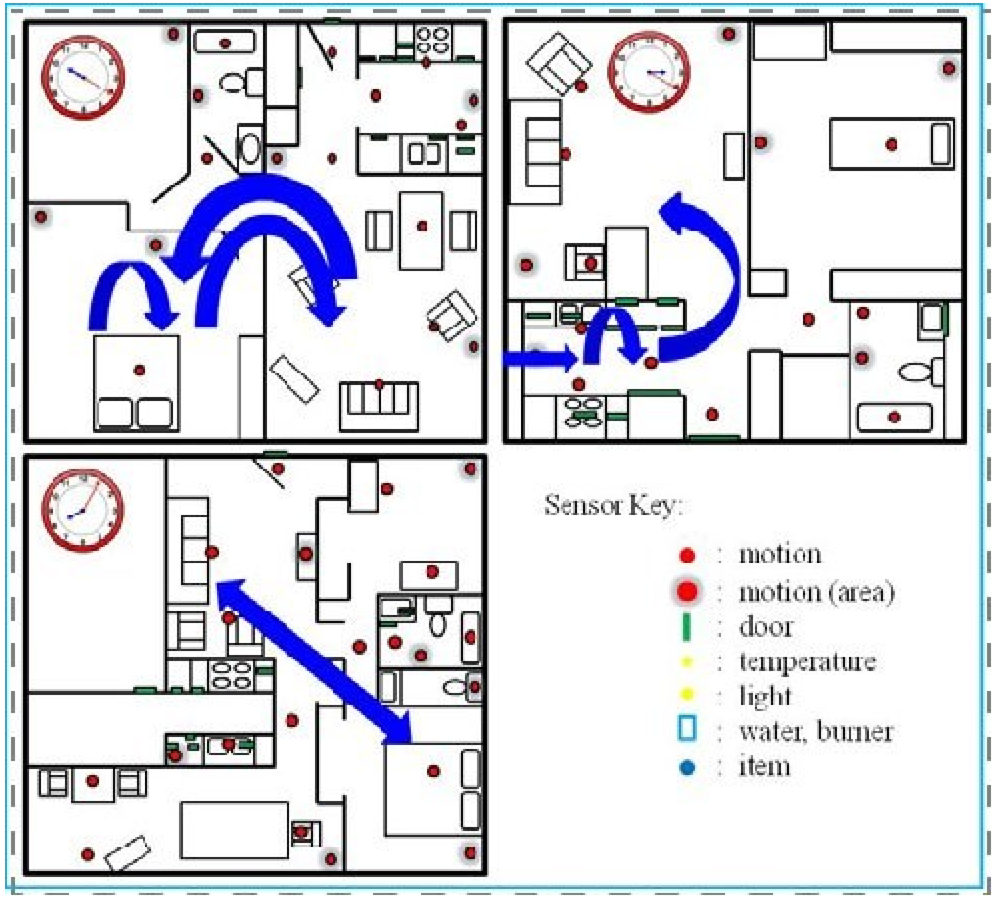
Sensing methods: *ambient sensors*

- Ambient motion detectors, contact switches, break-beam sensors, and pressure mats are used to **detect ambient changes due to human activity** in a smart environment (e.g., home and workplace)

- Ambient sensors are frequently employed in **ambient assisted living** for supporting daily life monitoring and tracking of multi resident environments *



D. J. Cook, A. S. Crandall, B. L. Thomas and N. C. Krishnan, "CASAS: A Smart Home in a Box," in Computer, vol. 46, no. 7, pp. 62-69, July 2013

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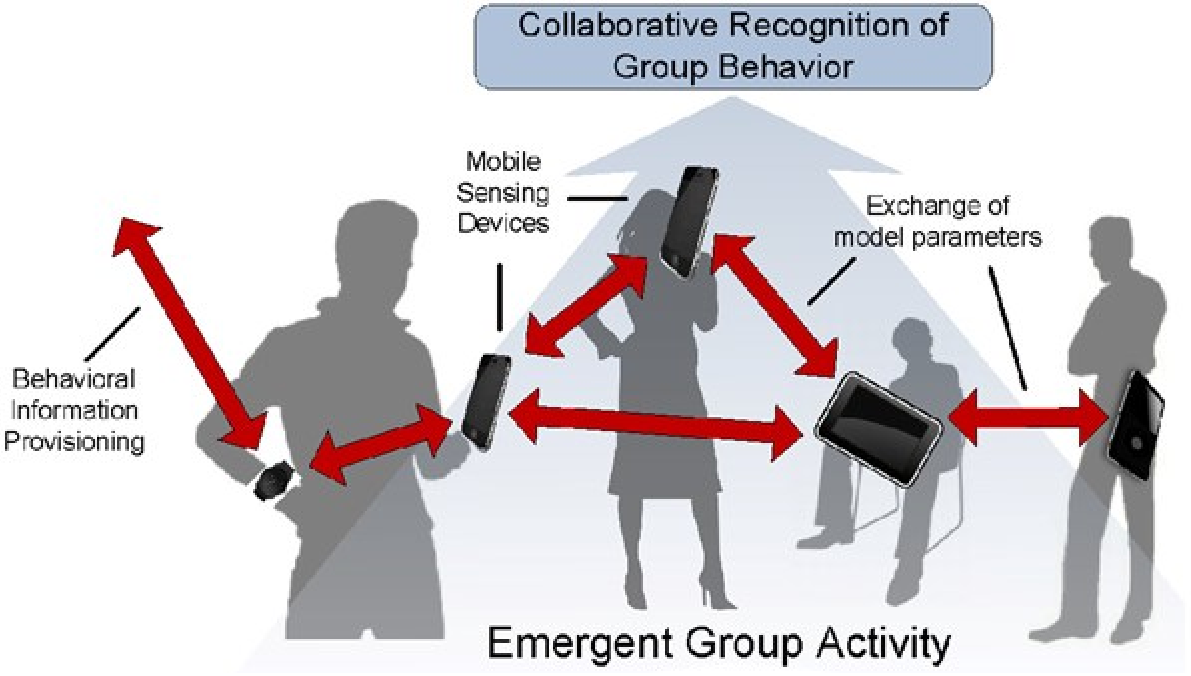
Sensing methods: *wearable sensors*

- So far, BSN and wearable sensors based activity recognition **focused on single-user HAR scenarios**.
- **MAR is challenging** due to the **complex nature of the interaction** dynamics and the **need for collaborative recognition** (or data exchange among users devices, at least).
- **Body-worn acceleration sensors** can be used to detect collective behavior patterns
- **Inertial sensors can be deployed in shoes** for detecting the gait pattern of users and recognize different groups based on the walking pattern and the proximity between different subjects *
- **Smartphone-based recognition** was used for **military group training** by recognizing and coordinating group and individual group member activities **
- **Physiological sensors** are also used to recognize multi-user activities. Handshake gesture was detected with a collaborative approach based on wrist-worn inertial sensors and heart-rate sensor to assess emotion reaction ***



* Q. Li , R. Gravina , S. Qiu , Z. Wang , W. Zang , Y. Li , Group walking recognition based on smartphone sensors, in: EAI International Conference on Body Area Networks, Springer, 2019, pp. 91–102 .

** A. Mukherjee et al. SmartARM: a smartphone-based group activity recognition and monitoring scheme for military applications, IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS), 2017

*** G. Fortino, S. Galzarano, R. Gravina, W. Li, A framework for collaborative comput- ing and multi-sensor data fusion in body sensor networks, Inf. Fusion 22, 2015

Recognition methods: *data-driven approach*

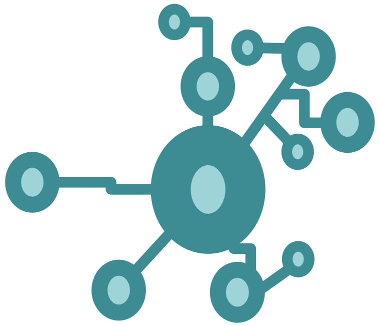
Category	Algorithm	Activities
Hidden Markov Model	Standard HMM	multi-person activities
	CHMM	two-occupant collaborative and interacting activities
	PHMM	different groups activities, concurrent activities
Conditional Random Field	CRF	multi-resident activity at home
	FCRF	multi-occupant activities, interaction
	SCCRF	concurrent and interleaved sub-activities
Artificial Intelligence	DNN-based	group activity
	hierarchical graphical model	
	hierarchical RNN	sport activity
	LSTM	intra-group and inter-group interactions
	convolutional relational machine	sport activity

Recognition methods: *knowledge-driven*

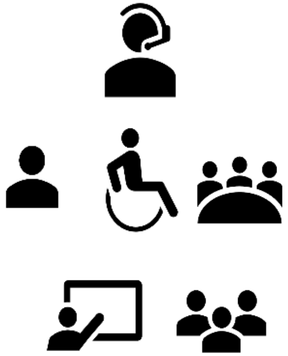
Category	Algorithm	Activities
Context information	semantic subsumption reasoning algorithms	multi-resident activity at home
Commonly-agreed knowledge	statistical techniques in similarity measure and approximate matching	multi-user concurrent activity
Semantic information	interactions modeling	intra-person interactions and inter-person interactions
Ontology-based	Activity ontology models	multi-user activities

- **Knowledge-driven approach** is an emerging method for MAR that **exploits information from domain knowledge** and **uses context information to specify the semantic relations of activities**.
- **Context** is typically the **location, identity, and state** of people, groups, and cyber-physical objects.

Open Challenges

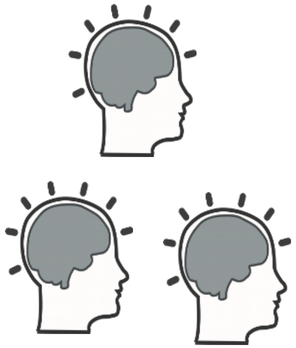


multi-sensor collaboration data acquisition and synchronization



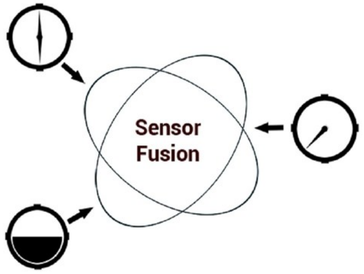
human-to-object and human-to-human interactions

group identification and recognition



multi-user activity prediction

Complex scenarios with interleaved or concurrent activities



Information is extracted and fused from distributed location across multiple devices

design wearable sensors to capture user interactions

From Collaborative BSNs to Edge and Cloud: BodyEdge

A Collaborative BSN Edge/Cloud architecture for multi-user activity recognition

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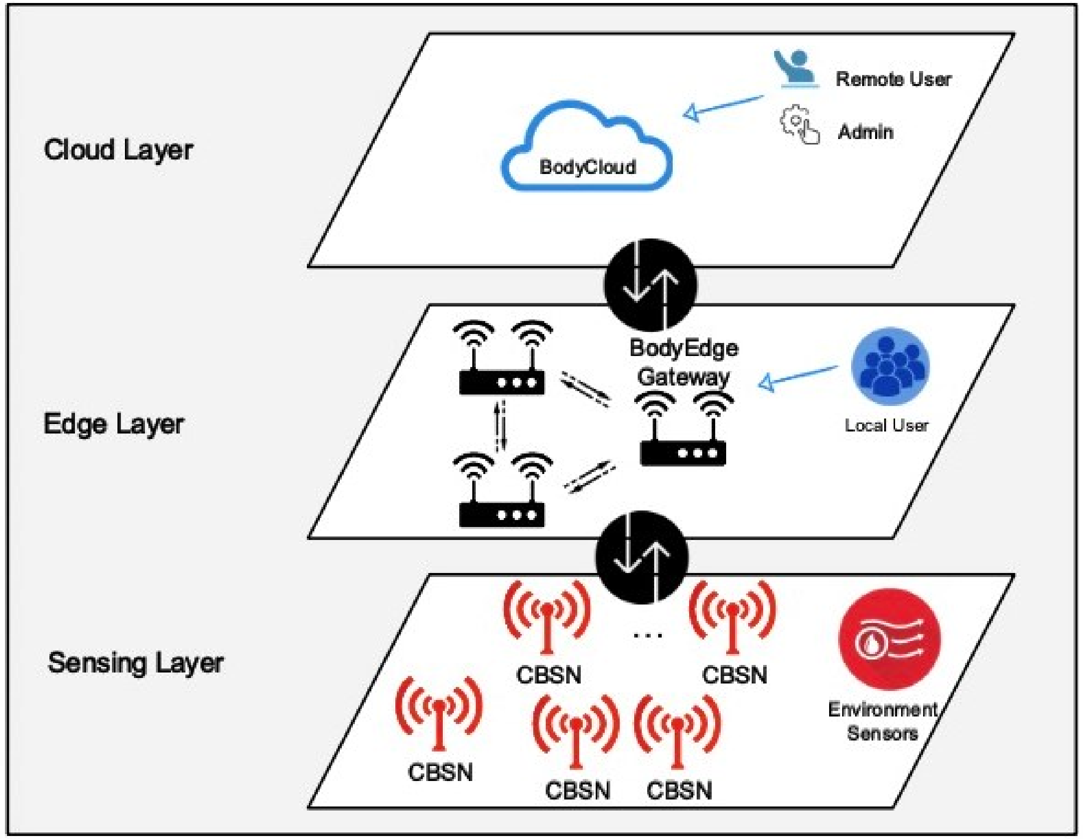
- The proposed approach **combines cloud and edge computing resources with C-SPINE** to process large amounts of data
  - Flexible computation allocation and deployment
  - Improved responsiveness
  - reduced communication latency
  - scalability
- **General-purpose design principles to support collaborative domains**, such as contextual interaction, group activity, recognition, affective and cognitive computing.

❖ *EDGE LAYER*
- receives features & individual activities
- identifies group activity & membership

❖ *CLOUD LAYER*
- connection to *CLOUD backend* only if *EDGE* computing is not available



A Collaborative BSN Edge/Cloud architecture for multi-user activity recognition

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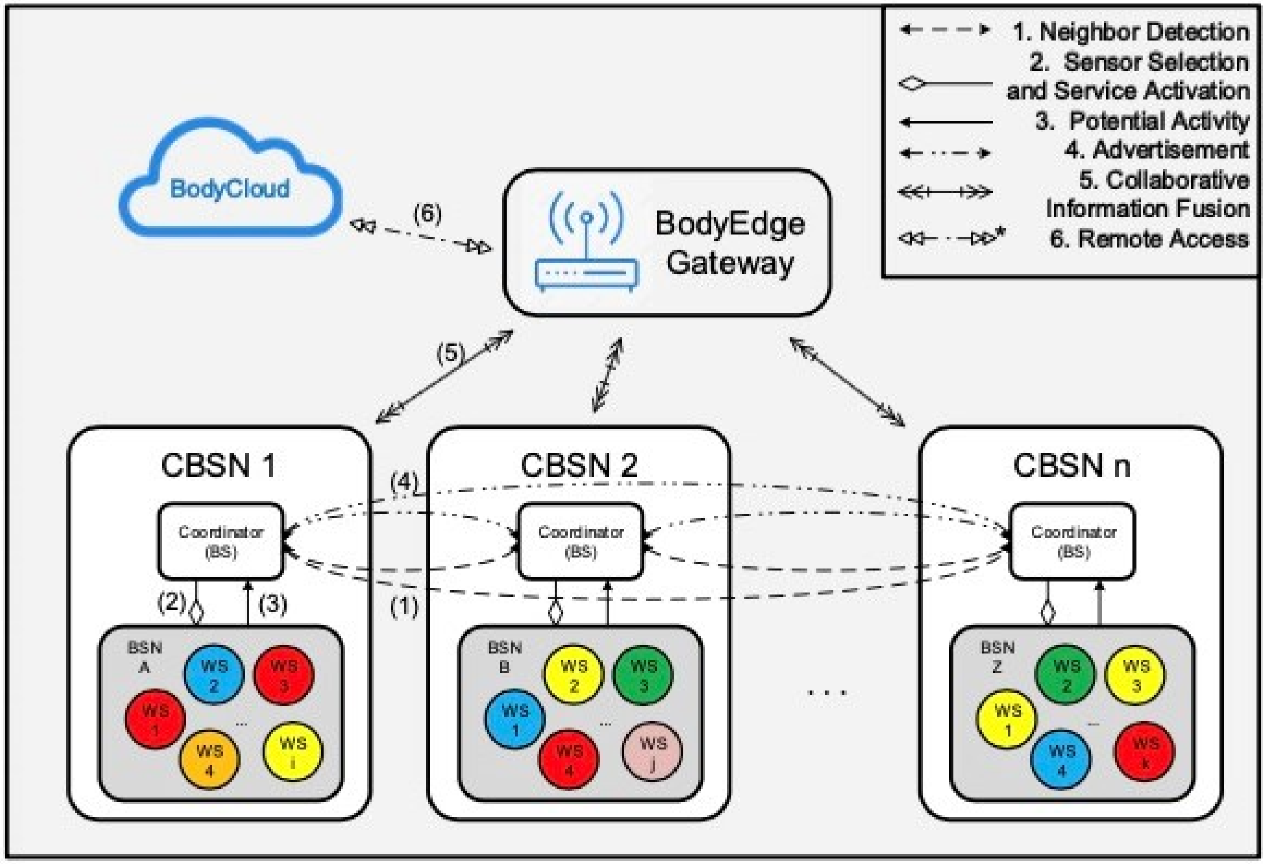

1. Neighbor Detection: it detects neighbor CBSNs among co-located people in a specific range.

2. Sensor Selection and Service activation: when neighbors have been detected, all of BSNs will activate/select sensing on their own nodes and necessary (processing) services will be enabled.
   Sensing and processing are activated only when it is needed.

1. Potential Activity: once a one-sided potential activity occurs on a BSN, the corresponding BS will be notified.

2. Advertisement: the coordinator will send a message to all neighbor CBSNs to request if there is a corresponding reaction for detecting multi-user activity.

3. Collaborative Information Fusion: low-level data and recognized individual activity will be sent to BodyEdge; the edge layer will perform decision-level fusion according to specific classification algorithms to detect the multi-user activity.

4. Remote Access: if large amounts of data are needed for computation or storage, the BodyCloud layer will provide proper support.

Thanks for your attention!

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