Visualizations of Human Activities in Sensor-enabled Ubiquitous Environments

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***Abstract*—Sensor network ubiquitous environments may generate a lot of data including heterogeneous 'raw' sensor data, low-level feature and/or trend data and higher-level context and inferenced information. This paper considers the visualization of such large, heterogeneous and complex integrated information, especially for real-time deployments facilitating rapid understanding leading to decision making. Visualizations are contextually structured according to the newly proposed Serviceable Visualizations paradigm for service-based and cloud-enabled visualizations. Specific visualizations of human activities are subsequently developed. These visualizations are based on the data provided via a secured WSN-integrated Cloud Computing for u-Health Care (SC3) architecture that is under development.**

I. Introduction

Sensor network systems deployed in ubiquitous environments have the potential to generate very large amounts of streamed, bursty, heterogeneous and complex information. Sensor acquired data often consists of multiple spatial-temporal data that may be scalar, vector, image and/or video data. Post processing of such 'raw' information including filtering, feature analysis and trend analysis leads to additional low-level information. Higher-level context and inferenced information derived by autonomic context and reasoning processes about the sensed data further generate additional information. Moreover, other more static data sets such as historical or context data may be combined with the sensor and sensor-derived information. At the same time, information filtering, fusion, or aggregation may reduce the data set size albeit introducing additional complexities in the semantics of the overall data set. In addition, sensor acquired 'raw' data is susceptible to noise or corruption due to sensing and communication limitations in realistic ubiquitous deployments.

Such large, heterogeneous and complex data often leads to difficulties in presenting specific useful information to the user communities. Often, only a 'useful' subset of information is needed; and the 'rest' of the data becomes 'clutter'. Moreover, privacy and confidentiality of some of the data may preclude certain parties in the user communities from viewing that data. In particular, decision- or policy-making in mission-, time- or life-critical applications require sufficient available salient information. In many applications, it is likely that ubiquitous application user communities would need access to pieces of data from this combined data set; such access is often facilitated by visualizations based upon queries. Furthermore, purely autonomic inferencing and reasoning systems may not be able to provide sufficient reasoning accuracy for mission-, time- or life-critical environments where very high accuracies of low-to-high- level information is required.

Incorporating visualizations aimed at facilitating understanding leading to decision making for these types of environments provides a mechanism for user communities to 'see' selected parts of the overall data set as well as provides an additional failsafe in the system. The issue of integrating these two visualization purposes in the context of the very large and widely varying input data sets aimed at multiple roles in a particular environment and generalizable to multiple environments poses a significant challenge to research and development.

Serviceable Visualizations is a recently proposed paradigm [1] whereby monolithic visualization methodologies of either local or remote visualizations are replaced by model- and service-packaging of visualizations. A demand-supply user environment drives the economy of Serviceable Visualizations enacted though a Diversity Exchange. A light-weight client framework on the end-user platform completes the system. This organization of visualizations is suitable for cloud and grid computing. As the demands for visualization increase driven by larger and more prolific deployments of sensor network ubiquitous systems, the wide-scope, ad-hoc and un-designed visualization requirements challenge current-day monolithic approaches to visualization and necessitate future developments of suitable on-demand visualization approaches.

This paper is a 'bringing-together' of some of the necessary 'ingredients' so to organize a comprehensive and consistent approach to visualizations of sensor network-based ubiquitous environments. This paper specifically deals with human activity visualization approaches. The rest of this paper is organized as follows. The next section, Section II, discusses the information sources and summarizes the ubiquitous sensor network architecture used in this work to provide the human activity-related data. Section III describes the visualization approaches in the context of the Serviceable Visualizations paradigm. Section IV exemplifies several on-going visualiza-

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tion developments. Conclusions are given in Section V.

II. Architecture

The primary sources of information are the sensor data streams. Typical data characteristics are: high data rates (hundreds of samples per second), bursty streams (samples taken at regular intervals for specific durations), and heterogeneous information (environmental, imagery, video, audio). Sensor acquired information also have physical placement (GPS coordinates, latitude and longitude) and is time-ordered. Sensor acquired data may contain corrupted information due to limitations in sensor operation, communication interference and other noise. Further discussion of sensor acquired data characteristics and surveys are available in [2].

Lower-level filtration and feature extraction seek to identify relevant information and reduce the effects of noise. Trend analysis seeks to identify simplified models of time-dependent data behaviors. Often, visual output of sensor data together with these lower-level information is shown as a time-dependent plot (e.g. see the multiplot in Figure 8). Animations are also used.

Higher-level context human activity reasoning seeks to identify micro- to macro-activity levels by integrating and inferencing from sensor data perhaps combined with other static information sources. Micro-activities in this paper refer to component-part activities such as arm or leg movement, mid-activities refer to whole-part activities such as walking whereas macro-activities refer to in-situ activities such as taking medication. Reasoning synthesizes new information that is partially outside of but overlaps with the context domain of the sensor data; that is, the data characteristics of the new information may include physical and environmental interactions, conceptual-level information, time dependent data, multiple-dependent data, and physical location in the environment.

A ubiquitous sensor network architecture is used that provides the human activity context of the visualizations considered in this paper as well as forms the testbed for future studies and applications. Specifically, ubiquitous life care (u-Life care) becomes more attractive to computer science researchers due to a demand on a high quality of care services at anytime, anywhere with a low cost. Many works exploit sensor networks to monitor patients health status and movements to provide care services to them. It requires sensory data to be quickly processed and transmitted to Internet so that physicians, clinics, and other caregivers can access conveniently. Most existing life care systems rely on their own data centers to store and process sensory data. It brings a high cost to maintain the system, yet the performance is not reliable and a limited number of services can be provided. This architecture is proposed and developed for a Secured WSN-integrated Cloud Computing for u-Health Care (SC3). A number of issues are considered including security and privacy for sensor networks, efficient delivery mechanism of sensory data to the Cloud, security for the Cloud itself, and dynamic collaboration among Cloud providers. To enable u-Life care, a new method of user activity recognition and ontology engine to detect user motions is proposed. Further details are discussed in [3].

The system workflow is shown in Figure 1. First, sensed and video data are captured from sensors and cameras, then are transmitted to the home Cloud Gateway. The Gateway determines the type of data based upon the sensor data characteristics and stores it in a Local Database. Then, classified data is forwarded to the Filtering Module where unnecessary data is filtered before forwarding it to the Cloud to increase the communication performance. Filtered data is also updated to the local database for later use. If there is a query from the services/applications, the Query/Response Manager queries data from the local database and responds to the requesters. However, neither the Filtering Module nor the Query/Response Manager are currently implemented. Data is transmitted to another part of the Cloud via a TCP/IP socket. Here, the raw data is used to deduce user activity and context, for example, a patient is walking, eating, or staying in the kitchen. Activity and context are then forwarded to an ontology that represents it in a convenient manner and an ontology engine deduces higher level activity and context data. The ontology engine also makes responsive decisions in some context, for example, if a patient is reading a book, then, the television should be turned off. When doctors, nurses, etc., wish to access the data, they must first authenticate themselves. After successful authentication, the Access Control module makes decision whether his/her access permission is allowed or not. If yes, it allows him/her to access to the Cloud data. And, data is forwarded to authentic nurses and doctors.

In terms of system data storage requirements, the large datasets generated by the sensor streams are likely not long-term achievable and hence visualizations need to be generated on-demand. Moreover, real-time requirements for mission-, time- and life-critical applications suggest that the 'raw' data streams combined with the low-level processed information are equally important as the higher-level context information which may not be so readily available. The two information sources therefore have different time availabilities.

In Figure 1, the raw data is obtained either from the gateway as a data stream or as 'raw' data files stored in the cloud (not shown). The higher-level information is obtained from the Ontology Engine shown in the middle of the cloud box. Visualizations are enabled to the end user communities via a web interface shown at the top of the figure (the visualization model(s) not shown).

III. Approach

Serviceable Visualizations require plug-in model definitions on-demand made available through a Diversity Exchange. Formal modeling of such visualization service packaging is beyond the scope of this paper; an intuitive packaging is instead considered. Figure 2 illustrates the overall organization. The data sources from the sensors to the Activity Engine relate with the data flow from the sensors through the gateway to the cloud in the testbed architecture. The activity engine performs the higher-level reasoning as shown in the testbed architecture and

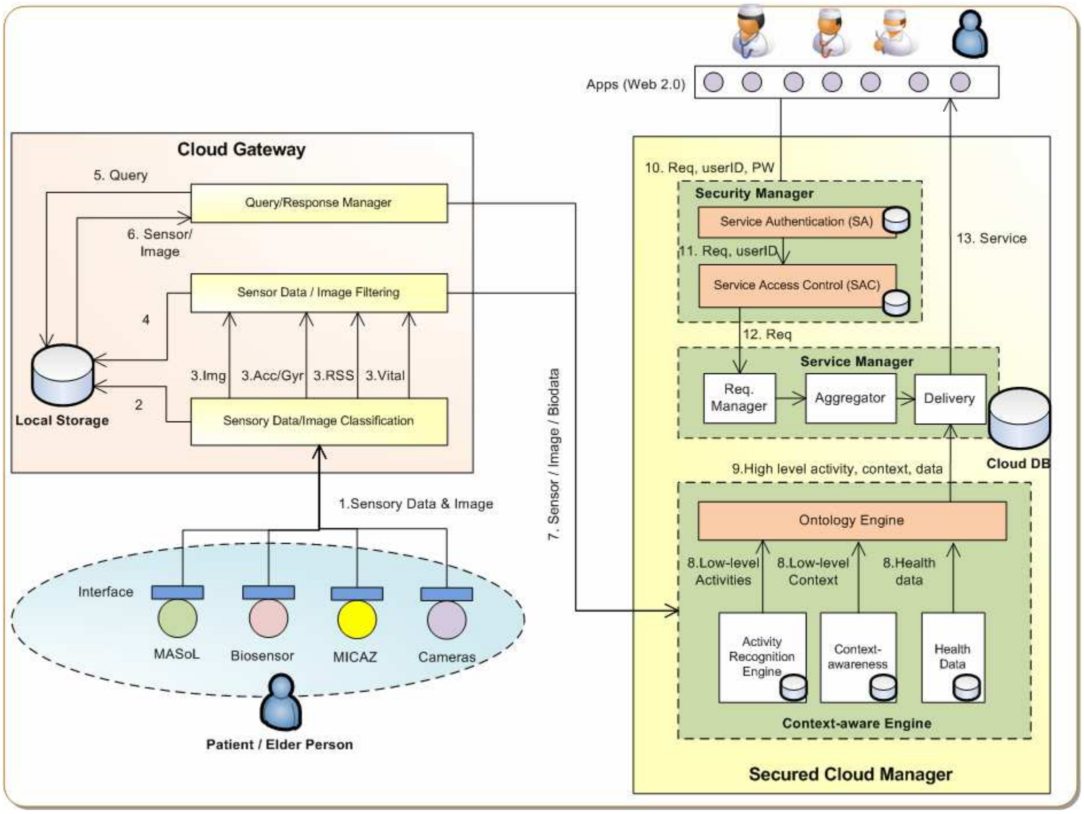

Fig. 1. System data flow overview.

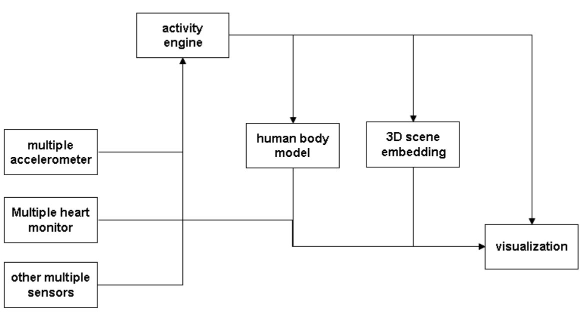

Fig. 2. Component organization: sensor data streams (left) go to visualization model to be embedded into the visual context models (center); low-level feature extraction and trend analysis combined with higher-level activity reasoning are performed by the activity engine and integrated with the context models, lastly, the visual context models are combined with activity and sensor data visualizations.

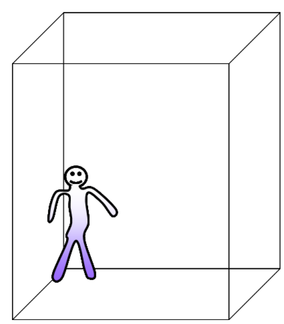

Fig. 3. Three dimension scene and human body visual context information - artist's drawing

the results of which are stored and accessed via the Ontology Engine in the architecture.

The activity information characteristics suggest that new domain contexts are needed in which to embed the visualizations (i.e. to provide visual context). New domain contexts are provided by the context models (in Figure 2, specifically human body model and 3D scene model) and the reasoned activity information is combined with these models. Lastly, the visualization obtains each of the context models, and the two information sources. Feedback from the visualization (not shown in this diagram) can be included to adjust the activities being performed (such use would be a part of the ubiquitous application based on decision-making of the visualization user community).

Figure 3 is a low-fidelity artist's drawing illustrating the visual contexts provided by the human body and 3D scene models.

IV. Visualizations

Pre-attentive visual processing involves no higher-level conscious thought whereas non-pre-attentive processing involves cognitive tasks. Therefore, displaying information in a way to facilitate pre-attentive processing (hereafter referred to as pre-attentive visual elements) promotes faster assimilation of

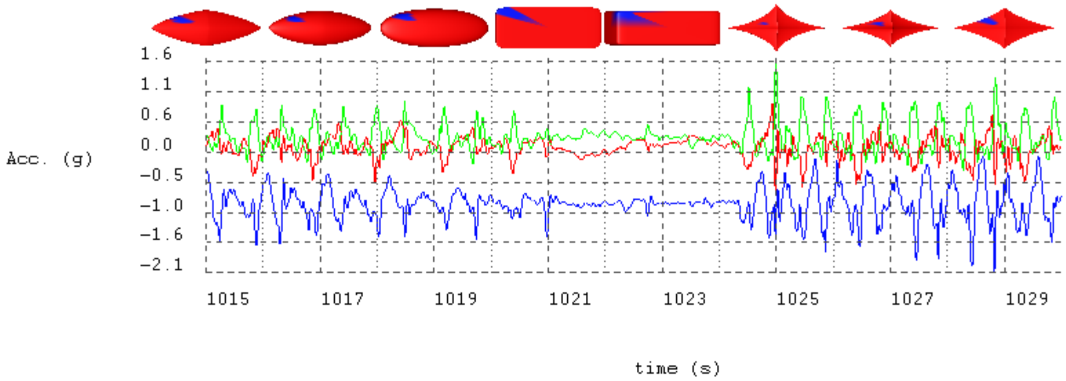

Fig. 4. Detail level Visualizations supporting pre-attentive and non-pre-attentive visual processing: the plot is a typical tri-axial accelerometer multi-plot showing 15 seconds of data, 75 samples per second (data set courtesy of Prof. Jun Jo, Griffith University, Australia), the shapes shown at top display the one second behavior trends on a shape scale of: square-corners – non-violent, rounded-corners – moderate and pinch-shaped corners – violent.

important data set characteristics. Notably, in human activity visualization, the change from one activity to another and the change in the characteristics of the activity (e.g. behavior), are important markers that should be visually presented as pre-attentive visual elements. However, detail often available from the filtered sensor data streams, is best presented in non-pre-attentive elements.

In [4], a superellipsoid-based glyph is proposed as a pre-attentive visual element (i.e. based on shape visual processing) that can sufficiently well capture useful information about time-dependent three-plot data. The earlier work concentrated on merely establishing the user perceptive qualities of such a method. Here, these superellipsoid-based glyphs are integrated with the detail time-dependent plots to provide for combined pre-attentive and non-pre-attentive visualization. See Figure 4. The superellipsoids shapes are ordered as square-corners – non-violent, rounded-corners – moderate and pinch-shaped corners – violent; and are determined by a low-level trend analysis (in this figure, based upon a normalized standard deviation calculation over a window period of one second normalized over the entire 15s dataset). The x, y, and z shape sizes are based on the amplitudes of the corresponding sensor data values (in this figure, the averaged values over a window period). The blue-spot represents the averaged vector of all three plots. The figure shows the superellipsoid glyphs positioned over the corresponding detail plots (i.e., the first left glyph is for the one second period from 1015–1016s, the next glyph to its right is for the period 1017–1018s, and so forth). The data set itself is from a human-mounted tri-axial accelerometer; this multi-plot shows 15 seconds of data, 75 samples per second (data set courtesy of Prof. Jun Jo, Griffith University, Australia). Clearly seen in this visualization is that the activities transition from moderate to non-violent to violent. Note, the multiplot of this data set also have the characteristics of pre-attentive visual elements, that is, the wave patters are easily 'chunked' into three wave shapes that are readily identified; however, in general, the wave patterns would not be so convenient.

The detail time-dependent plot, the superellipsoid behavior glyphs, the human body context and the 3D scene context are individually combinable in orthogonal ways constrained by physical locations. Some examples of such orthogonal combinations are: a tri-axial accelerometer mounted on a human could be shown as a superellipsoid behavior glyph attached to the human body figure; luminosity data plotted versus time could be shown as a plot at the location in the 3D scene; or, the human body figures showing human-related mid-activities could be combined with the time-dependent plots. Such combinations may be defined on-demand as requested by the user community. Other visualization models may also be incorporated. These described in this paper and others would be implemented as cloud-enabled service packages and could be down-loaded on demand; subject to constraints in combining the various visualizations. In addition, the afore-mentioned time availability issue regarding the more immediately available raw and low-level data versus the later available high-level data can be accommodated by this plug-in approach.

Typical visualization navigation techniques such as zooming and scrolling are used to navigate though large data set visualizations that do not conveniently fit on an output device. For the purposes of the multiplot time-dependent visualizations, three dimensional projection techniques of such 2D plots following the methods in [5] provides an additional method of display for large data sets.

An experiment was conducted [personal communication with Mr. La The Vinh] on April 21, 2009 at approximately 14:47 hours. The experiment consisted of a subject eating while sitting down in the experiment room. A single sensor attached to the right wrist of the subject recorded tri-axial accelerometer data. The sampling rate was 20 samples per second. The real-time sensor data was captured in the local data base in the Cloud Gateway in flat-file format of 128.05 seconds of data. No filtering process was involved. Since this data set was subsequently used for training purposes, the visualization study here already consists of labeled activity data. Therefore, this study does not incorporate data from

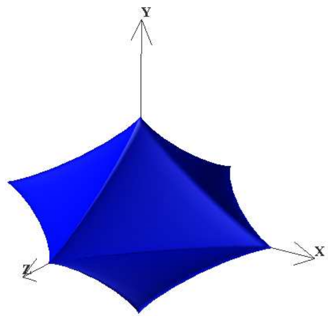

Fig. 5. Example of the transition from unknown activity to eating; the behavior is slightly violent indicating that the subject may not be in a fully comfortable pose for eating.

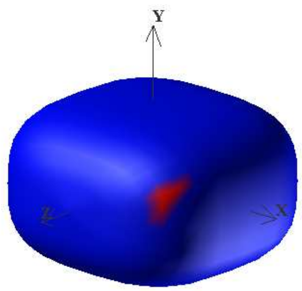

Fig. 6. Example of the last oscillatory behavior pattern's first of two indicated behaviors; the red spot (front-center) indicates the acceleration vector.

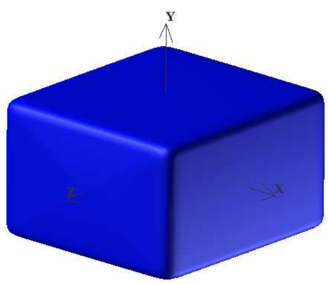

Fig. 7. Example of the last oscillatory behavior patterns second of two indicated behaviors.

the activity recognition processes. Furthermore, the first 16 seconds of data correspond with some unknown activity; the remaining data corresponds with eating.

The visualizations studied here consist of a two-second time window frame analysis with a small positive offset (+1) to ensure that the accelerations (in units of g-force) along each access is always greater than zero.

Interesting, there are two different behavior patterns observed: first, for the period of 16 seconds to 20.6 seconds, somewhat moderate to violent behavior pattern occurs, exemplified by the slight pinch shape glyph in Figure 5. Beyond 20.6 seconds, the behavior patters transitions (in less than 5 seconds) to an oscillation pattern between moderate and non-violent behaviors; and, the non-violent behaviors begin to dominate over time. Figures 6 and 7 exemplify this pattern for the last oscillation (which is the least violent of all). In most cases, the angle of acceleration is fairly constant at about 45 degrees on the x-z plane and elevated roughly 30 degrees on the y-axis. Overall, the behavior patterns suggest that the subject is less relaxed at the start of the eating activity but becomes more relaxed and comfortable as time progresses. On September 11, 2009, the subject was shown the above visualizations (including others not included in this paper) and confirms that the indicated behaviors as interpreted from the visualizations are accurate [personal communication with Mr. La The Vinh]. The tri-axial multiplot in Figures 8 and 9 details the raw sensor data corresponding and consistent with the interpretations from the shape visualizations above.

Lastly, a high-fidelity visualization composed of the 3D scene of the room in which the eating activity occurred together with a pair of behavior shape images (corresponding to the latter two figures) indicating the identifiable eating behavior patterns is shown in Figure 10. Here, only the behavior shapes are embedded for illustrative purposes.

Several important visual elements such as color and animation are not specifically considered in this paper. Color is highly useful to represent data attributes and is often a function of the specific application. Moreover, the use of color should be consistent across the incorporated visualizations and constrained by suitable color design (e.g. adjusting hue and luminosity for red-green color mapping). Animation is highly useful to show specific trends, usually over time and again, is more useful left as a function of the specific application.

There appears to be few notable research projects dealing with human activity visualization. GIS map-based visualizations are often used for location tracking (see [6]) or other spatial aspects (see [7]), and may include three dimensional contouring (see [6]). Icons illustrating activities or showing the environmental context of the activities have also been used (see [7], [8]). A parallel coordinate-based visualization approach is described in [9] for mixed activity behavior and environmental information. The use of 3D scenes to provide visual context is not new. Recent work includes mixed-reality (real combined with virtual worlds) [10].

V. Conclusion

This paper considers preliminary steps to identify and organize a visualization approach suitable for current and future sensor network ubiquitous system deployments. Visualization of such large, heterogeneous and complex integrated information is challenging; especially for real-time deployments facilitating rapid understanding leading to decision making. The approach considered is consistent with the recent Serviceable Visualization paradigm and enable plug-in visualization models that can be parameterized on demand. Various visualizations that exemplify this approach for raw sensor data, low-level trend analysis and higher-level context and inferenced information is considered. This preliminary work 'sets-the-stage' for future visualization research and development leading to prototype development.

An architecture for sensor-acquired information, gathering, storage, reasoning and management is also described. This

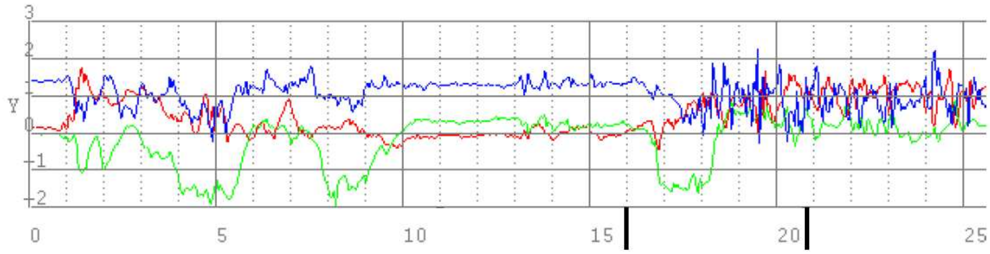

Fig. 8. Tri-axial multiplot showing the first 25 seconds of data, note the three regions of behavior (g-force (g) vs. time (s)).

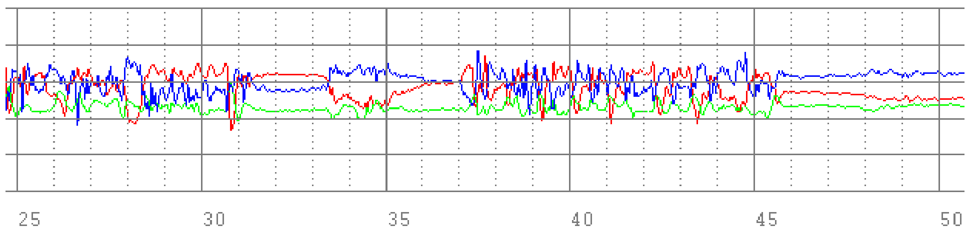

Fig. 9. Tri-axial multiplot showing the 25 to 50 seconds of data, note the two oscillation cycles that are shown (g-force (g) vs. time (s))

Fig. 10. A visualization of the 3D scene composed with behavior shape images; the approximate location of the eating activity is chair-height back-left of the image and where the shape glphys are placed.

forms the basis for future research, development and implementation of suitable methods for human activity recognition.

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