An RFID-Based Position and Orientation Measurement System for Mobile Objects in Intelligent Environments

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***Abstract*—Ambient Intelligence considers responsive environments in which applications and services adapt their behavior according to the user's needs and changing context. One of the most challenging aspects for many applications in Ambient Intelligence environments is location and orientation of the surrounding objects. This is especially important for effective cooperation among mobile physical objects in such smart environments. In this paper, we propose a robust indoor positioning system that provides 2D positioning and orientation information for mobile objects. The system utilizes low-range passive Radio Frequency Identification (RFID) technology. The proposed system, which consists of RFID carpets and several peripherals for sensor data interpretation, is implemented and tested through extensive experiments. Our results show that the proposed system outperforms similar existing systems in minimizing the average positioning error.**

***Index Terms*—Ambient Intelligence, Smart Environment; RFID; Location and Orientation measurement**

I. Introduction

IN Ambient Intelligence (AmI), Information and Communication Technology is expected to become ubiquitous as millions of computers are getting embedded in our everyday environments [1]. Such advancement has opened a new era for context-aware computing where applications are required to become accustomed not only to the computing and communications constraints and resources, but also to the contextual information such as objects in the surrounding and people and activities in the environs, and even emotions and other states of users. Context-aware applications are capable of obtaining contextual knowledge in order to allow users to access a wide variety of services that are tailored on specific desires and preferences, according to the conditions in the smart environment [2]. Examples of context-aware applications of smart environments include intelligent offices or digital homes, as described by IST Advisory Group [3]. A typical example of such environments is described in section II. In this paper, we focus on context-aware applications in indoor smart environments where multiple mobile physical objects exist and are expected to cooperate among each other to provide the user with a customized service according to the surrounding context. Mobile objects are objects in the environment for which their location and/or orientation could change for different reasons, such as chairs, tables, carts, etc., or objects that do not move that often such as couches and beds. In all cases, we need to determine the position and orientation of the objects to be aware of their location in case they are moved. In such environments, context-aware applications can only adapt their behavior while collecting and adjusting information for the user if the objects' position and orientation is estimated with an appropriate grain-size. This paper takes upon the challenge of determining the location and orientation of mobile objects in indoor environment by proposing a robust and novel system based on passive RFID technology.

Our proposed system consists of RFID carpets and several peripherals for sensor data interpretation. RFID tags are widely recognized for their distinctive advantages with respect to their low cost and identification capability [4]. They are also known for their promising potential in context-aware applications. Furthermore, passive RFID tags have practically no lifetime limit because they do not require batteries to maintain the wake-and-query cycle that active tags use [5]. In our system, described in details in section IV, RFID tags are mounted on carpet pads where the mobile objects are placed. The system is designed to work for objects that are connected, directly or indirectly, to a point which is at a short distance from the ground. The RFID tags are placed on fixed, pre-defined positions within a specific carpet pad. The tags do not store any position information except their row and column coordinates within the corresponding carpet on which they are mounted. This special component-based design allows us (at low cost) to dynamically extend the RFID carpet for covering arbitrary large spaces. Moreover, this design allows us to manipulate the density of RFID tags on different partitions of the carpet to minimize the error and to separately control specific areas of the carpet in order to meet specific application needs.

While the open literature describes different approaches for localization and orientation, our system outperforms existing systems in minimizing the average positioning errors. Furthermore, existing techniques for indoor localization such as vision sensor or WiFi based approaches are often sensitive to changes within the environment. For exmple when metal objects are moved from one place to another within the environment, change in the electro mag-

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netic fields happen which significantly influences the robustness and precision of wireless positioning approaches. Another example is the changes in lightig conditions or the reflection of infrared signals by objects in the environment. This change affects the precision and robustness of camera based tracking systems. One of the major advantages of RFID technology over vision based or other sensor based methods is that reading RFID tags does not require line of sight, making RFIDs immune to problems associated with occlusion. Another major advantage of RFID technology is that it is standardized, widely used, robust, and cheap. The cost of an RFID tag is very low, therefore even for applications that require large number of RFIDs the cost is not an issue. Because of the unique and strategic advantages of RFID tags, they have been heavily investigated in numerous applications (e.g. [6], [7], [8], [9], [10]).

We cover the related work in more details in section III. Inspired by the problem scenario explained in the next section, our system is validated by a proof-of-concept implementation and tested through extensive experiments. The main contributions are as follows: First, our system outperforms existing systems in minimizing the average positioning and orientation errors. Second, the system design is scalable while the cost remains controllable without affecting the error margin. As it will be explained later in the paper, the system can be extended to cover arbitrary large spaces by simply adding more carpet pads at low cost (few cents per RFID). Furthermore, the average error for any given area is controllable simply by increasing or decreasing the density of the tags of the corresponding carpet pad(s) which covers that area. And because each object calculates its own position and orientation based on 1 to 4 RFID tag positions, the computational complexity does not increase. Thus, the average error is neither affected by the covered area nor by the number of available objects in a specific carpet area that autonomously calculate their own position.

The rest of this paper is organized as follows: In the next section, we describe an example problem scenario to better familiarize the readers with intelligent environments and to describe their requirements. In section III, we discuss the related work. Section IV describes the approach and the system proposed in this paper, followed by the system validation in section V. Finally, in section VI, we conclude the paper and present plans for future work.

II. PROBLEM SCENARIO AND REQUIREMENTS

In this section, we present a scenario for an indoor intelligence environment where multiple physical objects need to cooperate together to provide the users with a customized service according to the surrounding context. The aim here is to describe a typical problem related to objects localization and orientation in indoor smart environment settings and the solution to this problem as addressed by the proposed system in this paper. The scenario is as follows:

Consider that a group of co-workers, Alice, Bob, and Jack, are planning to get together and discuss their project in one of the company's conference rooms. Alice wants to present her slides and Bob needs to show a video about a prototype he has developed. The project manager, Jack, wants to discuss the project's financials and provide some statistical data. The intelligent room offers a set of displays and rendering devices: two smart boards, a mobile TV station, as well as audio rendering devices. In addition to the worker's personal computers, there is a digital projection system mounted on the wall. Let us also consider that the TV, which would be a better choice for video rendering, is exposed to sunshine because the window's curtain has been dismounted to be cleaned. Therefore, using this device may not be a good choice in this specific context. Figure 1 illustrates this example scenario.

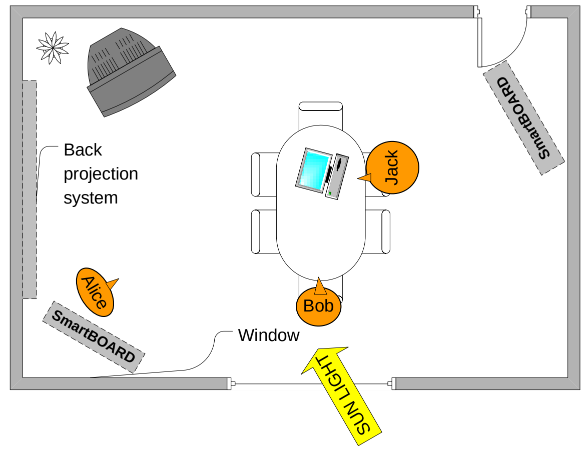

Fig. 1. Example scenario of a smart room

While coarse-grained localization, that is, whether an object is present or absent in the proximity, is sufficient for many applications, in the above scenario the intelligent room requires fine-grained localization and must be able to recognize the surroundings and present the media to the users on the best suitable devices proactively.

It is expected to utilize and orchestrate available media input and output devices and sensors in order to maximize the multimedia experience and to support the user's activities. For example, one smart board presents the slides and the other plays the video. The financial visualization takes place on the smart board as soon as the slides' presentation is finished. The personal computers will be showing the slides and allow cooperative annotation as well as personal notes. The main question regarding this context-aware multimedia presentation is how the content can be delivered to users, while at the same time accounting for the various types of context information discussed above. This problem is known as intelligent media output coordination [11], [12]. The main challenge to the realization of such applications is the correct determination of the changing contextual characteristics of the environment [13], [14]. That is, determining the position and orientation of persons and objects for the purpose of having the best suitable device present a given media content. Surveys of some of the indoor positioning approaches and systems are found in [15], [4]. The open literature has also described few other complex systems such as those of [13], [9]. Such systems provide positioning information with an average error between 30 to 300 cm. However, for smart applications such as the one we just described, it is required to localize objects with much lower error. Furthermore, intelligent output coordination requires defined information about the position and orientation of users and the potential rendering targets such as displays [11]. Based on the existing surveys and the scenario explained above, we can list the requirements of such environments as follows:

A. Measurement error and uncertainty

For effective realization of intelligent multimedia environments, positioning and orientation of objects should be measured with minimum error. The best measurement so far is attained by Hile and Bornello [16] where the average error is about 30 cm. In other systems, such as Ubisence [17], the errors range between 50 to 150 cm. Lorincz and Welsh [7] presented a system where the error could vary between 80 to 160 cm. Our work, on the other hand, provides positioning and orientation data with an average error of 6.5 cm with standard deviation of 4.5 cm for positioning measurement and an average error of 1.9 degrees with standard deviation of 2.5 degrees for orientation measurement.

B. Affordability and standard compliancy

To ensure that further development is compatible and easily integrated in the system, it is important that the positioning technology be based on well developed standards so that off-the-shelf components are used. Furthermore, extension to existing systems should be achieved at low-cost. Luckily, the cost of RFID tags is only a few cents, that is, even an RFID infrastructure consisting of thousands of tags would only incur a small cost. Such characteristics guarantee wider acceptance and adoption of our system.

C. Object Scalability and Mobility

The system should support rooms of different sizes. Furthermore, the number of objects to be positioned should be scalable. In addition, the calibration effort should be minimal as new objects are added or existing objects are moved or removed. Many existing indoor positioning systems allow only a limited number of objects to be positioned in parallel, and thus are not arbitrarily scalable. This is especially so for indoor positioning systems that are vision-based or those that use ultrasonic sensors. In the former, hidden objects are invisible to the system; in the latter signal interference limits the system's scalability. Other systems that utilize active RFID tags to measure the position of mobile objects also face scalability challenges as the computational complexity increases with the increased number of objects in the environment.

As we will show later in the paper, our system satisfies all the above requirements. Furthermore, the system is scalable and the computational complexity does not increase as the number of objects increase in the environment, because each object independently calculates its own position based on 1 to 4 RFID tags.

In the next section, we cover some of the existing systems and demonstrate that they do not meet at least one of the above requirements.

III. RELATED WORK

In this section, we describe four commonly used approaches for indoor positioning and orientation that are representative and specifically related to our work. Although far from being exhaustive, this section gives a rather complete idea of the current state of the art. It should be mentioned here that this paper focuses on indoor environments only and therefore works related to object positioning and orientation for outdoor environments are skipped.

A. Beacon-based Approaches

Beacon-based systems for object positioning in intelligent environments have been proposed in the literature for their low cost and low energy consumption. An example of such systems is introduced by Roy Want et al. [18]. Their approach consist of an Active Badge location system which utilizes a network of beacons communicating with pulse-width modulated IR signals in order to locate users in intelligent office environments. Bahl et al. [21] developed the RADAR system which is an RF-based beacon system for indoor user positioning and tracking. Other approaches have also been proposed for indoor positioning systems that utilize radio frequency or Ultra-Wide-Band technology [17] to determine the user's position. Some other special types of beacon-based systems use Wi-Fi technology [22]. An extensive survey of these studies can be found in [23]. However, a common issue in beacon-based systems is that the user is required to carry an additional device in order to allow the system to locate him or her. Another issue is that using radio frequencies makes the reliability of the whole positioning system very dependent on different variables related to shapes of objects, materials, etc., that are found in the environment, because RF signal propagation is influenced by phenomenon such as reflection, diffraction, diffusion, and absorption. Therefore, extensive calibration is required for such systems. Another limitation of beacons-based systems is that beacon or tags cannot be embedded inside metallic objects such as mobile smart boards or Hi-Fi boxes. Also, for some critical applications in special environments, such as tracking medical surgery equipments in hospitals, the use of radio frequency may interfere with equipments and therefore it is not permitted.

B. Camera-based approaches

The use of camera and computer vision such as the work presented in [13], [24], is another approach. Yan et al. [24] present systems for measuring 3D position of users in indoor environments ceiling-mounted cameras. A common problem with camera-based positioning is that environment models or object information such as human

TABLE I
ANALYSIS AND COMPARISON OF EXISTING SYSTEMS

Reference	**Application Domain**	**Approach**	**Average Precision**	**Scalability**	**Issues**
Hile and Borinelloe [16]	Indoor Navigation	Image-based	10cm-150cm depending on runtime and availability landmarks; average is 30 cm after 6 seconds runtime	scalable	Very low speed: 9 seconds from the time of taking the image to calculate the camera position; privacy issues; depends on lighting conditions
Ando and Graziani [8]	Navigation for visually impaired	Infra-red sensors	N/A	Not arbitrarily scalable	Issues with hidden objects, signal reflection
Roy Want et al.[18]	Generic	Beacon-based	NA	N/A	RF signal propagation is influenced by phenomenon such as reflection, diffraction, diffusion, and absorption
Ubisense [17]	Generic	Beacon-based (Ultra-Wide-Band)	50cm..150cm depending on the environment; 30 cm only in optimal conditions such as the center of the sensed space	Theoretically up to 150 tags	Very expensive and requires continuous calibration; building material and other objects in the environment influence precision and accuracy
Krumm et al. [13]	Generic	Camera-based	N/A	Not scalable for parallel objects positioning	Computational complexity, sensor calibration; not scalable for simultaneous positioning of a high number of objects
Zhou and Shi [19]	Robot tracking	Passive RFID	N/A	Scalable	Fixed objects are excluded as they do not provide velocity data
Lorincz and Welsh [7]	Generic	Beacon-based (sensor nodes)	0.8m - 1.6m; can go up to 3.3 m depending on the variance of obstructions. Beacon node failure, radio signature perturbations, and beacon node density	Not arbitrarily scalable	Sensitive to radio interferences and signature perturbations; precision and accuracy highly depends on surroundings objects' material
Willis and Helal et al. [20]	Indoor Navigation for visually impaired	Passive RFID	works with absolute position information	Arbitrarily Scalable	absolute position information written on tags that are deployed on landmarks. Repositioning of tagged objects requires re-writing of RFID tags. No orientation data.
Presented work in this paper	Object positioning and orientation	Scanning labels, passive RFID	6.5 cm average positioning error and 1.9 degrees average orientation error	Arbitrarily Scalable	Designed for objects with small distance to the floor

face models is required to detect and recognize objects before their position can be determined. Furthermore, vision based systems require line of sight in order to establish a connection with the objects and locate them. Such limitations make it very hard to apply this technology in order to detect arbitrary mobile objects in complex environments. Hile and Borriello [16] developed a system for positioning and orientation in indoor environments based on camera phones. The system processes images taken by a cell-phone camera and matches them to predefined landmarks inside the environment such as corners, floor-to-wall transitions, doors, etc., to calculate the camera's location. While helpful for individuals with cognitive impairments, the positioning approach is not suitable, as mentioned by the authors, for large rooms and open areas that do not provide enough edges, corners and landmarks. Moreover, in environments such as open exhibitions where landmarks change frequently due to the ad-hoc nature of the facility, pre-processed landmarks cannot be used.

C. RFID-based approaches

Recently there are many approaches that take advantage of the emerging mass production of very small, cheap RFID tags [25], [20]. The work presented in [20] is somehow close to our work in utilizing passive RFID tags for object positioning and localization. In such system, the position of each tag, the relative position of the surrounding objects, and other supplementary information in the room are stored in each tag. The system also tracks the moving person using RFID-mounted shoes.

While the system in [20] requires equivalent amount of tag writing as the proposed system in this paper, in our case it is done only once. Willis and Helal in [20] store in the RFID tags the absolute position information and the semantic information about surrounding objects to help visually impaired people navigate freely. The drawback of their design is in the massive rewrite to the stored data in the RFID tags in case the objects are removed or the surrounding environment changes. In our system, however, we made sure that if the whole carpet is moved within the room or the global coordinates of the room change (e.g. rearranging the walls in a flexible office) we do not need to update the stored information in the RFID tags. Instead we only change the reference vector pointing to the origin point of the carpets' local coordinate system. This vector is not stored in the RFID tags but (currently) managed by each mobile object as global context information. The vector is used to perform coordinate transformation.

Similar to the work presented in [20], Yeh et al. [26] propose an RFID-mounted sandal to track people in indoor environments. Yeh et al. [26] developed a system based on infra-red sensors that adapt smart signal processing to provide users with information about the position of objects hindering their path. Multi-sensor strategy for locating and tracking objects is also used in the work presented in [8].

Contrary to these works, the RFID tags in our system do not store data that refer to their position. Instead the data in the tags correspond to the row and column numbers within a carpet plate which integrates those RFID tags like a grid. By so doing, we can move the carpet plate to any place in the room without the need to change the stored data. This makes our system unique compared to the above mentioned approaches. For example, in [20] it would be very costly to update the data stored in the tag if the spatial geometry of the room changes. Such scenario is often the case for modular offices, multipurpose buildings, exhibitions, and conference rooms with mobile walls.

D. Other approaches

Parallel to the above mentioned solutions, other approaches such as SmartFloor [27] and Smart Carpets [25] are also developed. SmartFloor uses person-specific step patterns to locate users on carpet elements using pressure sensors. The system must be able to take into account the weight changes of the person that happen over time. The main issue with this approach is that mobile objects of the same type (eg, mobile TV stand, or smart board) exhibit the same step pattern that cannot be distinguished and tracked easily. Smart Carpets, on the other hand, are commercial products equipped with a network of self-organizing micro-controllers. These embedded micro controllers are not pertinent to object tracking in the same way as RFID-based systems.

Ashokaraj et al. [28] developed a multi-sensor system to measure the position and orientation of a four wheeled robot based on ultrasonic signals using interval analysis. Ultrasonic sensors are integrated around a robot giving low level information affected by noise, bias, outliers, etc. to detect obstacles. However, this approach requires that a 2D map describing the surrounding environment with its landmarks and obstacles be provided to the robot a priori.

While a system like [28] relies on the robot's movement and velocity to predict and track the robot's position, it is interesting to note that in intelligent environments, position estimation based on velocity is not always possible. Furthermore, why "estimate" or "predict" when we can get a more precise reading from cheap RFID tags and less computational complexity? Also, velocity-based estimation or "dead reckoning", as it's sometimes called, is not really appropriate for the scenario described in this paper. The reason is three-folds: First, velocity-based estimation would require velocity measurements, which would increase processing and measurement complexity. Second, when objects are lifted and carried from one place to another place, tracking their movement based on their velocity would not be possible before putting them down on their final position. Third, in such applications we only need the final position of an object, and we are not interested in the object's position as it is being moved. So all the computational resources used in velocity-based position estimation will be wasted as the object is in motion.

Other approaches such the work presented in [29] use sound analysis to detect the position of an object or human. The major shortcoming of such approach is that objects cannot be detected if they do not produce sound.

In summary and as shown in Table I, no system works optimally for all indoor cases and each has its own shortcomings. In this paper, we are not proposing that our system replace completely all other existing systems for all scenarios, but simply that for certain indoor scenarios, which are quite common, our approach has advantages over other approaches. In the next section, we provide the details of our proposed system.

IV. OUR APPROACH: POSITION MEASUREMENT BASED ON PASSIVE RFID TECHNIOLOGY

In order to meet the above-mentioned requirements, we have developed a system to determine the position and orientation of mobile objects based on passive RFID technology. Our system, as shown in figure 2, consists of RFID carpets, several peripherals for sensor data interpretation, and distribution of the positioning information.

A. RFID Carpets

In our approach, we require the RFID tags to be mounted on carpet pads where the mobile objects are placed. The pads are PVC isolation foils that are usually put on the floor. We placed a carpet on top of the foil. The carpet, as illustrated in figure 2, is composed of N by M pads which are equal in dimensions, such that $N; M > 1$. On each carpet pad, RFID tags are placed at location (X,Y) such that $X; Y > 1$. Each tag is placed on a fixed, pre-defined position within a specific carpet pad. In figure 2, the coordinates X and Y correspond to the row and column of the carpet pad. The tag stores the integer values x and y that are referring to the horizontal rows and the vertical columns respectively. The tag also stores the horizontal row variable m and the vertical column variable n that correspond to the pad's location within the room dimensions. It must be mentioned that the distribution of

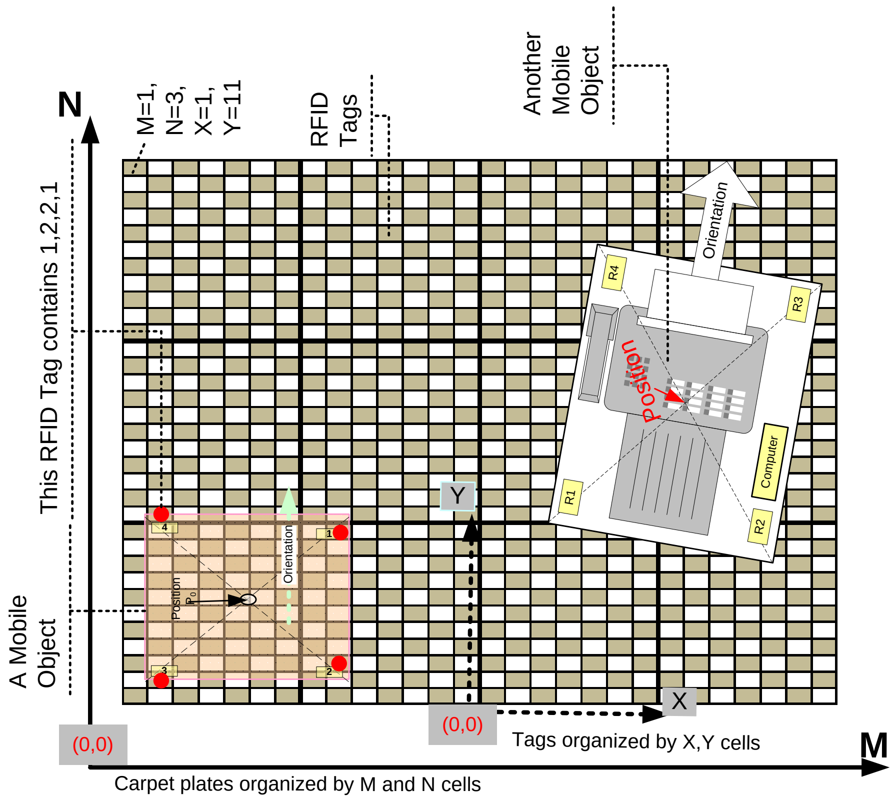

Fig. 2. An extensible RFID carpet composed of $n * m$ components with two mobile objects on it. The orientation has been defined to be an orthogonal vector to a side defined by the mobile object itself.

the RFID tags on each carpet pad does not need to be the same. However, it is important that the position information stored in each tag refers to the variable x and y in relation to the design as shown in figure 2. In our design, we made sure that if a change is required in the distribution (for example, fewer RFID tags in the carpet) then it is done by skipping rows or columns as required, but not changing the cell index (X and/or Y) of the RFID tags. By so doing, we avoid changing the stored data in each RFID. Furthermore, we can manipulate the density of RFID tags on different partitions of the carpet to achieve the desired resolution and to separately control specific areas of the carpet in order to meet specific application needs. We can also extend the RFID carpets for covering arbitrary large spaces.

B. Mobile object setup

In our setup, we have mounted RFID readers on all mobile objects, , an example is shown in figure 4. The RFID reader components are connected to an embedded computer via the serial interface through which the position and orientation information are calculated based on the stored tag information. Since the distance between the reader and the transponder must be small, we have installed the readers under the mobile object.

C. The distribution of tags

The arrangement of the tags is selected in a manner that only one tag can be covered from a reader. The main reason for that is the expected resolution and reliability of the position results. While theoretically it is enough to have one reader per object that can read one RFID tag to calculate its position, at least two readers need to detect two RFID tags to calculate its orientation. And because orientation is very important for our application, two readers are not always enough since they would not necessarily match with the tags. For example, if the tags' distribution is very sparse, then the probability of getting a reader in an untagged zone is high and thus it receives no positioning data. Therefore, using more readers per object increases the systems' robustness and ensures measurement quality in terms of lower average error.

D. Measurement method

The overall measurement steps are as follows: *Scanning* the transponders read out the tags in a synchronized manner. The tag's ID, the value for the coordinates $M, N, X, and Y$ are time stamped and forwarded as a data tuple $< M, N, X, Y >$ to the software module.

Measurement of Parameters: the software module calculates the position of the object based on the data tuple $< M, N, X, Y >$, the RFID tag's ID, and the time stamp. This information is scanned from the RFID tag

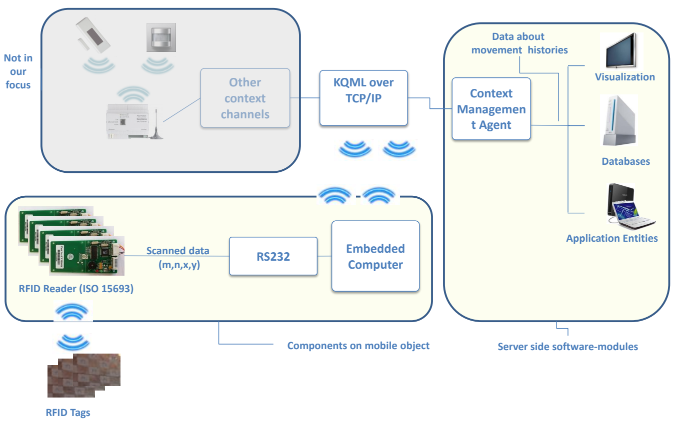

Fig. 3. Module components of the RFID system

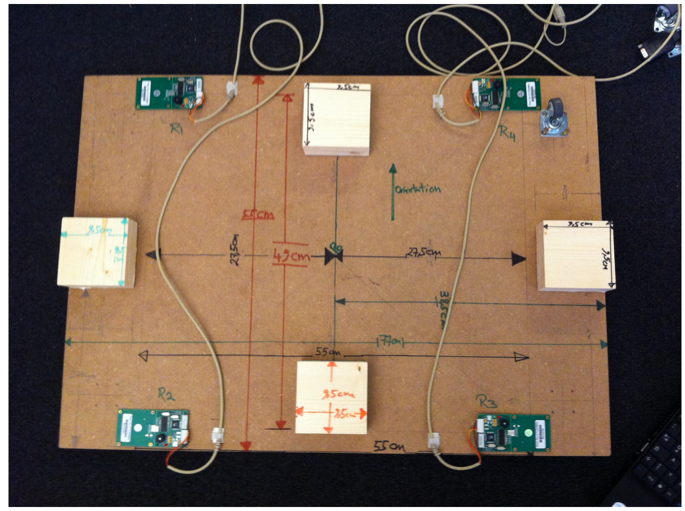

Fig. 4. Actual placement of the RFID readers on the mobile object

which is close to the specific reader.

Communication: The system's component modules are shown in figure 3. The inter-communication among them is as follows: When the data is scanned, the embedded computer translates the measured information into high-level "context events" and sends it to the software modules. The software modules consist of a context management agent and a database which stores the mobile objects' movement history. In this setup, the embedded computer is part of an agent communication module. It uses the Knowledge Query Markup Language (KQML) which offers a plain-text based TCP/IP agent communication mechanism to interact with the entities in the system.

An alternative approach would have been to send the RFID reader output using a wireless serial adapter such as Bluetooth, ZigBee, or WiFi, to a remote computer. Each RFID reader would need to be connected to a wireless serial adapter that is paired to a remote computer in the room. While such approach could save on energy consumption of the mobile device by just operating the wireless serial devices, it produces signal interferences, especially if there are more than 2 or 3 mobile objects in a room. That is, 12 wireless serial adapters will operate in the same room using the same remote computer.

E. Determination of position and orientation

In order to calculate the position of a tag which is scanned by a particular reader we use the following formulas:

$$P_x = (m-1) * SecW + (x-1) * TraW + \frac{TraW}{2} \tag{1}$$

$$P_y = (n-1) * SecH + (y-1) * TraH + \frac{TraH}{2} \tag{2}$$

Note that m, n, x, and y are all digits greater than 0. The sybmols in equation (1) and (2) are described in Table II.

For cases where we cannot scan a tag, the x and y components of P are not determined. The above equations show that with two location points, we can determine the position and the orientation of an object. However, to increase the robustness of the system we have used four readers. If one or two readers fail, the system can still effectively calculate the position and orientation of the mobile object.

The position of the mobile object is determined by the center point P_0 as shown in figure 5. The Z-component of the 3D position can easily be calculated from the height of the mobile object. The orientation of the mobile object changes only around the z-axis (yaw). The center point P0 is calculated by building the vectorial average of the n identified reader positions:

$$\vec{P_0} = \frac{\sum \vec{R_i}}{n} \tag{3}$$

where $i = 1..n$ such that $1 \leq n \leq 4$, $\vec{P_0}$ is the middle point of the mobile object, and $\vec{R_i}$ represents the vectors (points) calculated based on the data received from the readers.

However, if the size and dimensions of the mobile object are known, the position can be calculated by using only two points using the length of the mobile stand or its diagonal as it is shown in figure 5. To illustrate that, consider the following cases: If $\vec{R_1}$ and $\vec{R_3}$ are known, then the position of the mobile object can be calculated using the following equation:

$$\vec{P_0} = \vec{R_1} + \frac{\vec{R_3} - \vec{R_1}}{2} \tag{4}$$

If $\vec{R_2}$ and $\vec{R_4}$ are known, then the position is the centre point between the line joining them which is calculated by using the following simple formula:

$$\vec{P_0} = \vec{R_4} + \frac{\vec{R_4} - \vec{R_2}}{2} \tag{5}$$

If we get the position from two readers, i.e. $\vec{R_1}$ and $\vec{R_2}$ or $\vec{R_3}$ and $\vec{R_4}$ as shown in Figure 5, then to obtain the middle point of the mobile stand we need the unit vector $\hat{u}$ between the points as well as the middle point $\vec{P_x} = \hat{u} * A/2$

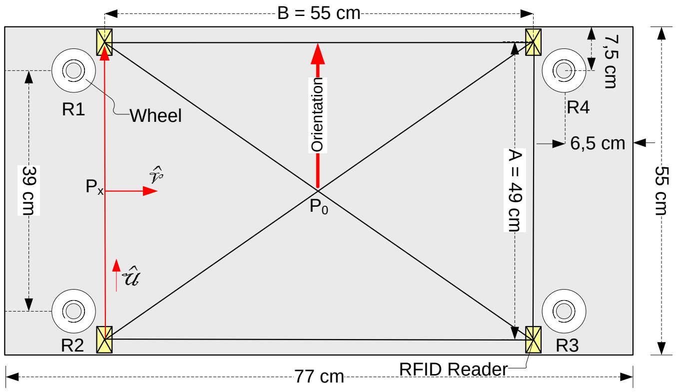

Fig. 5. Illustrated map for the size and dimensions of the mobile object with respect to the mounted RFID readers

TABLE II
GLOBAL CONSTANTS RELATED TO THE TAGS

Variable	Description
TraW	The width of the tag
TraH	The height of the tag
SecW	The width of the carpet's section
SecH	The height of the carpet's section

of the line connecting the two points. Then we need to rotate the unit vector $\hat{u}$ using the rotation matrix R_Φ and the formula $\hat{v} = \hat{u} * R_\Phi$. With this new unit vector we can obtain the position of the mobile stand by multiplying it with $B/2$ of the mobile object and adding it to P_x. Using $\vec{R_1}$ and $\vec{R_2}$ we can calculate as follows:

$$\vec{P_0} = \vec{P_x} + \hat{v} * B/2 = \frac{\vec{R_1} - \vec{R_2}}{||\vec{R_1} - \vec{R_2}||} * A/2 + \frac{\vec{R_1} - \vec{R_2}}{||\vec{R_1} - \vec{R_2}||} * R_\Phi * B/2 \tag{6}$$

whereby $\Phi = \pi/2$ or 90 degrees. Using $\vec{R_1}$ and $\vec{R_4}$ we have to use A instead of B and the rotation angle Φ will be $-\pi/2$ or -90 degrees. For the example shown in figure 4, the length of B is 55 cm and A is 49 cm. The orientation is seen as a normalized, orthogonal vector from the mobile object towards the center of a user-defined side of the objects. The "'unit"' vector of $(\vec{R_1} - \vec{R_2})$ or $(\vec{R_3} - \vec{R_4})$ is the orientation $\hat{o}$ of the mobile object:

$$\hat{o} = \frac{\vec{R_1} - \vec{R_2}}{||\vec{R_1} - \vec{R_2}||} \tag{7}$$

For the case when we only have the positions of and $(\vec{R_2}, \vec{R_3})$, the unit vector must be rotated in the right direction with an amount $\Phi = \arctan \frac{A}{B}$. If ($\vec{R_2}$ and $\vec{R_3}$) are known instead of $(\vec{R_1}, \vec{R_4})$, then the rotation angle will be $\Phi = \arctan \frac{A}{B} + \pi/2$. The following numerical example illustrates the above analysis:

Example: Consider the layout shown in Figure 2, assume that the readers R_1, R_2, R_3, and R_4 (marked in red) are detected and the data collected from these readers are as follows:
R_1 readings are (m, n, x, y) = (2, 1, 2, 11)
R_2 readings are (m, n, x, y) = (2, 1, 2, 3)
R_3 readings are (m, n, x, y) = (1, 1, 2, 2)
R_4 readings are (m, n, x, y) = (1, 2, 2, 1)

Applying equations 1 and 2 then we have for R_1
$P_{1x} = (2-1) * 60cm + (2-1) * 8.5cm + \frac{8.5cm}{2}$
$P_{1x} = 60cm + 8.5cm + 4.25cm = 72.75cm$
$P_{1y} = (1-1) * 60cm + (11-1) * 5.5cm + \frac{5.5cm}{2}$
$P_{1y} = 57.75cm$

Then, the position of the RFID reader R_1 is represented by the ordered set (point) $P_1 = (72.75cm; 57.75cm)$ or a 2 dimensional vector . Similarly, the positions for readers R_2, R_3, and R_4 are calculated and shown below. For R_2, $P_2 = (72.75cm; 13.75cm)$,
for R_3, $P_3 = (12.75cm; 8.25cm)$,
and for R_4, $P_4 = (12.75cm; 62.75cm)$

Applying equation 3 we get:

$$\vec{P_0} = \frac{\sum \vec{R_i}}{n}$$

$$= \frac{\begin{pmatrix} 72.75cm + 72.75cm + 12.75cm + 12.75cm \\ 57.75cm + 13.75cm + 8.25cm + 62.75cm \end{pmatrix}}{3}$$

$$\vec{P_0} = \begin{pmatrix} 42.8cm \\ 35.6cm \end{pmatrix}$$

The orientation of the object in Figure 4 is calculated based on the readings from R_1 and R_2 per equation 7 as follows:

$$\hat{o} = \frac{\vec{R_1} - \vec{R_2}}{||\vec{R_1} - \vec{R_2}||}$$

$$= \frac{\begin{pmatrix} 72.75cm - 72.75cm \\ 57.75cm - 13.75cm \end{pmatrix}}{\sqrt{0 + 44^2}} = \frac{\begin{pmatrix} 0cm \\ 44cm \end{pmatrix}}{44cm} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$\phi = 90deg$$

, since $x = 0, y > 0$.

The above example shows how the position and orientation of mobile objects are calculated according to the coordinates on the carpet itself. However, if the layout of the carpet is done in a way that it does not share the same coordinates with the room in which it is integrated, then we need an additional vector pointing at the origin of the carpet's local coordinate system that we add to the measured position vector. In addition, we have to map the measured position vector from the carpet's local system into the global coordinate system. This can be done by a coordinate system transformation. An alternative way is to arrange the carpet pads so that its origin point and unit vectors line up with those of the room. In such configuration, we can directly read out the absolute position according to the room's coordinates and not the local coordinates of the carpet. In other words, if the carpet's coordinates are lined up to the global coordinates of the room, then all the calculated positions are measured in reference to the global coordinates of the room. In this case, coordinate transformation is not needed. However, for flexibility and configuration re-usability it is preferred to use coordinate transformation, i.e., the case when the carpet tiles are not lined up with the coordinates of the room. The reason is that the carpets can be moved within the room or even relocated to other rooms. And for this, the software algorithm will only need the global position of the carpet's point of origin and the unit vector of its N axis. Any other point located on the carpet can be calculated and transformed to a point in the global coordinates of the room.

It should also be made clear that it is a characteristic of our system which has been specifically designed to optimally identify the location and orientation of objects that are connected, directly or indirectly, to a point which is about 7 cm to 10 cm from the ground. However, since each object connects to the ground in one way or another, this is not a shortcoming that cannot be overcome for most cases. For example, a computer monitor is usually on a table or stand and is rarely separated from it, so the tags can be put on that table or stand. When the monitor is put on top of another stand, the system can easily be configured to use the new stand's position to track the monitor.

In the next section, we provide implementation evaluation and analysis of our system.

V. VALIDATION AND TEST ANALYSIS

We validated our proposed approach by a proof-of-concept implementation which is used to analyze the average error for the mobile object's positioning and orientation measurements. The aim here is to show the feasibility of the system and its capability of reading the position and orientation data of mobile objects on-the-fly. The following subsections provide detail explanations about the system testing have that we have performed to analyze the measurement errors while the mobile object is moving from one point to another.

A. *Prototype Implementaion*

The highlights of the prototype are as follow: A mobile stand is equipped with four RFID readers. The dimensions of the mobile stand are as shown earlier in figure 4 and 5. We used a 60 cm x 60 cm carpet pads and then we placed the RFID tags on top of them. The RFID tags are arranged using a checker board arrangement as shown in figure 2 and 6. The RFID tags are Tag-it HF-I transponders made by Texas Instruments. The pads were organized in 3 rows and 5 columns and cover a surface of 3m x 1.80 m. On each pad we have placed 39 RFID tags. The size of the tags is 8.5 cm x 5.5 cm. We used *Mifare* QC-3100-AT RFID readers, which comply with the ISO 15693 standard. The readers

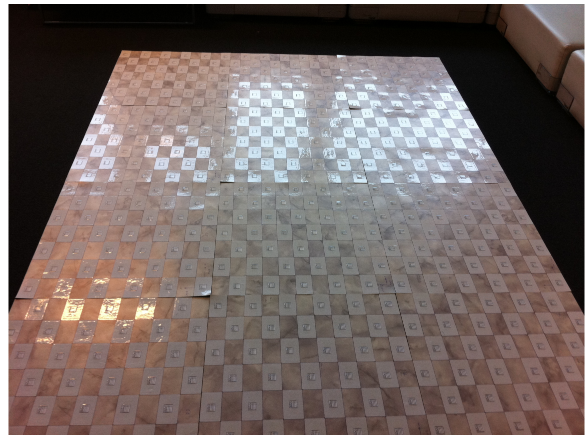

Fig. 6. Layout of RFID tags on the floor

were installed at a distance of about 4 cm from the edge of the lower part of the mobile stand. Through several trial experiments we were able to optimize the vertical distance of the readers from the ground in order to detect the tags even if they are not located directly under the readers. The distance is found out to be between 3 cm and 6 cm. The measurements of the constants described in Table II are as follows: TraW = 8.5cm, TraH = 5.5cm, SecW = 60cm, SecH = 60cm.

B. *Test setup*

Our experiment consists of two tests: The first test is based on a route that consists of 10 test positions (i.e. different locations and angles). In each run we used the four readers to analyze the data. In this test the mobile stand is moved along the edge of the carpet with random steps. Furthermore, we ensured that while we are moving the stand from one position to another along the edge, the orientation is always pointing to the same direction and in each step we slightly changed the position and the orientation left and right in a zigzag form. The reason for that is twofold: First, random steps allow us to test the robustness of the system while avoiding positions that have the same properties with respect to the location of tags and readers. Second, the zigzag form allows us to take different measurement for the orientation at each position. The total number of scans is as follows: 10 position x 4 readers = 40 scans. The second test is mainly used to analyze the measurement error pertained to the orientation of the object. We have placed the mobile stand in one location and rotate the stand 360 degrees in steps of 22.5 degrees. The results of the experiments are discussed next in subsections.

C. *Results and analysis of the first test*

Table III shows the test results of the first test and figure 7 shows the difference between the measured and the true location of the mobile stand center point.

In this test, for 7 of the 10 positions, the 4 readers were able to scan the tags, in the other 3 positions only 3 readers were able to scan tags. The reason could be attributable to

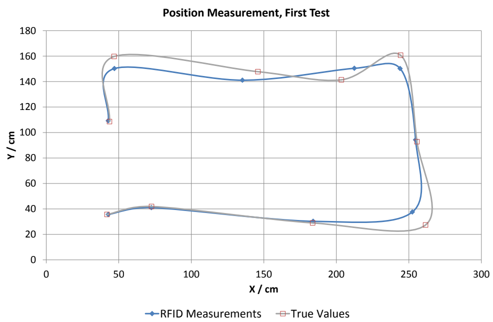

Fig. 7. Difference between the measured and true location of the mobile stand (average error 6.5 cm, standard deviation 5.4 cm)

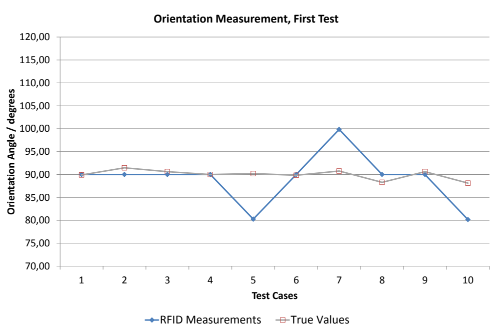

Fig. 8. Difference between the measured and true value for the orientation of the mobile stand (average error 1 degree, standard deviation 4.9 degrees

TABLE III
Positioning Results of the First Test (average error 6.5 cm , standard deviation 5.4 cm); MP: Measured Position in cm; TV: True Value in cm; Err: Localization Error in cm (Vectoroial Distance)

Pos.	MP_X	MP_Y	TV_X	TV_Y	Err
1	42.8	35.6	41.9	35.6	0.9
2	72.5	41.0	72.6	41.9	0.9
3	184.0	30.3	183.7	29.0	1.3
4	252.4	37.6	261.5	27.4	13.6
5	254.6	94.3	255.6	92.8	1.7
6	244.0	150.3	244.3	160.7	10.5
7	212.4	150.4	203.5	141.4	12.7
8	135.3	141.1	145.9	147.8	12.6
9	47.0	150.3	46.8	159.7	9.5
10	42.8	109.3	43.6	108.6	1.1

TABLE IV
Orientation Results of the First Test. Average error 1 degree, standard deviation 4.9 degrees. (MO: Measured Orientation; TO: True Orientation; Err: Orientation Error)

Pos.	TO/degrees	MO/degrees	Err/degrees
1	89.90	90.00	-0.10
2	91.46	90.00	1.46
3	90.63	90.00	0.63
4	90.00	90.00	0.03
5	90.21	80.26	9.95
6	89.84	90.00	-0.16
7	90.76	99.84	-9.08
8	88.29	90.00	-1.71
9	90.62	90.00	0.62
10	88.13	80.16	7.97

signal collision or interference or that simply there were no tags under the reader. In Table III, the results show that the range of measurement error was from 0.9 cm to 13.7 cm (absolute value of the vectorial differences). The average error is 6.5 cm with a standard deviation of 5.4 cm. Table IV shows the analysis of the mobile stand orientation for the first test, and figure 8 shows the difference between the measured and the true orientation for each test position. The orientation error ranges between -9.08 to 9.95 degrees with average error equal to 0.96 degrees and standard deviation equal to 4.92 degrees. In figure 8, we notice that at positions 5, 7, and 10, the orientation error is higher than the other 7 test postions. This is mainly due to the fact that unlike position calculation where we take the vectorial average of 4 readers positions, for orientation calculation we use only two readers. In the position calculation, the effect of the error contributed by one reader is minimized when averaged with the other 3 correct reader positions, while in the orientation calculation the error contributed by one reader is averaged by at most one other correct reader position. This is why we see the spike in figure 8 at positions 5, 7, and 10.

D. Results and analysis of the second test

In the second test, the mobile stand was centered in one location and rotated 360 degrees in steps of 22.5 degrees as shown in figure 11.

The mobile stand was rotated through 16 stages as shown in Table V. At each position, we measured the postion and orientation of the object and compared it with the true values. In the 16 orientation test positions, the error ranged between 0 and 9.8 degrees with average error equal to 1.9 degrees and standrad deviation equal to 2.5 degrees. At positions 3 and 13 in table V, we have noticed that the average error is higher than those tested at the other positions, this is mainly due to the case when the reader receives responses from several neighboring tags at one location. In this case, the reader selects one tag that might not be at the exact measured location and hence contributes to such higher error value. Figure 9 plots the difference between the measured and the true orientation

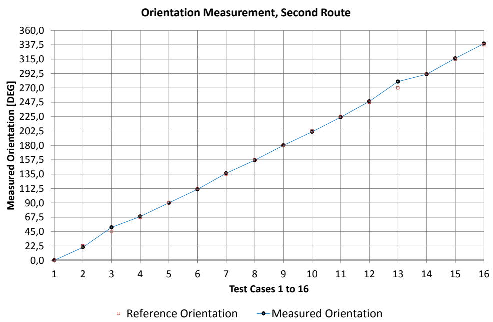

Fig. 9. Comparison of the true orientation angle with the measured angles in degrees in the second test (average error 1.9 degrees, standard deviation 2.5 degrees)

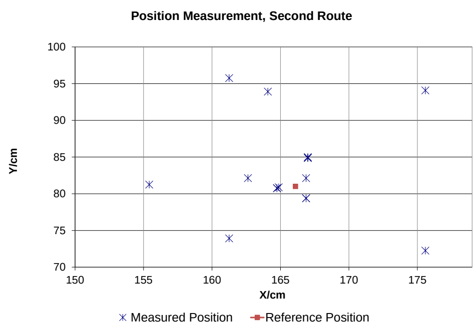

Fig. 10. Comparison of the true position with the measured value in the second test (average error 6.3 cm, standard deviation 5.3 cm)

angle. Table VI shows the measurement of the mobile object position with repect to the true value of the center point (166.1cm, 81 cm). The position error between the actual and the measured value ranges from 1.3 cm to 16.2 cm. The average error value equals to 6.3 cm and the standard deviation equals to 5.3 cm. Figure 10 plots the difference between the measured and the true position values. The total number of scan attempts is 64 (16 positions x 4 readers) among which 6 scans were not successful. Among the 16 test positions we had 6 test cases where 1 reader could not detect the RFID tags, namely at postions 1, 5, 11, 12, 14, and 15. At these 6 test positions, we noticed a higher positioning error than the average 6.3 cm shown in table VI. This is because the positioning calculation was done based on three readers instead of four.

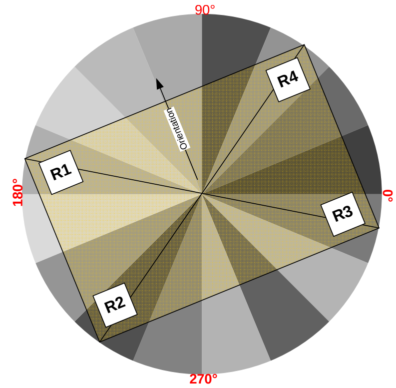

Fig. 11. Rotation of the mobile stand in the second test

TABLE V

Orientation Results of the Second Test. (average error of 1.9 degrees, standard deviation 2.5 degrees)

Pos.	TO/deg	MO/deg	Err/deg
1	0.0	0.0	0.0
2	22.5	20.4	2.1
3	45.0	51.6	6.6
4	67.5	68.7	1.2
5	90.0	90.0	0.0
6	112.5	111.1	1.4
7	135.0	136.3	1.3
8	157.5	156.9	0.6
9	180.0	180.0	0.0
10	202.5	201.2	1.3
11	225.0	224.1	0.9
12	247.5	248.9	1.4
13	270.0	279.8	9.8
14	292.5	291.3	1.2
15	315.0	316.3	1.3
16	337.5	339.4	1.9

VI. Conclusion and Future Work

The The goal of this paper was the development of an RFID-Based system for determining the location and orientation of mobile objects in smart environments with higher accuracey than existing sytem, while still reaminnig economically affordable. A number of contributions were made in this paper. Specifically, we have shown through a proof of concept implementation and a series of experiments that the system achieves a low average error for indoor object positioning and orientation, which are lower than the previous work as described in section III. For future work, we are planning to study the effect of using different types of floors. This is because the absorption rate of RF energy varies from one type of floor to another (e.g. wood floor, concrete floors etc.) and thus affects the measurement error of mobile object positioning and orientation.

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TABLE VI
Positioning Results of the Second Test. Average error of 6.3 cm, standard deviation 5.3. True Center point = (166.1cm, 81 cm). MP X: Measured Position X; MP Y: Measured Position Y; Err: Localization Error (Vectoroial Distance)

Pos.	MP X/cm	MP Y/cm	Err/cm
1	175.6	94.1	16.2
2	166.9	79.4	1.8
3	166.9	82.1	1.4
4	167.0	84.9	4.0
5	175.6	72.3	12.9
6	167	84.9	4
7	162.6	82.1	3.7
8	164.8	80.8	1.4
9	167.0	85.0	4.1
10	166.9	79.4	1.8
11	155.4	81.3	10.7
12	161.3	95.8	15.5
13	164.9	80.9	1.2
14	161.3	73.9	8.6
15	164.1	93.9	13.1
16	164.8	80.8	1.4

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