An Autonomous Proxemic System for a Mobile Companion Robot

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Abstract. **–** This paper presents an Autonomous Proxemic System (APS) for a mobile robot. It detects people in the surroundings and manipulates the robot's motions to approach them keeping an acceptable proxemic distance. The APS sensing functions include face and upper body detection, leg detection, and motion detection using camera, laser, and infra-red sensors respectively. The control functions consist of approach a human and obstacle avoidance. APS uses the sonar and laser range devices to keep an accurate proxemic distance with the human. Initial system tests indicate that the APS keeps desired proxemic distances to within an acceptable error margin.

1. Introduction

In order for a mobile service or domestic robot to be a socially acceptable and effective companion, it must exhibit appropriate socially acceptable behaviours. The study of social spaces between people is termed *Proxemics*. Within the wider research field of Human-Robot Interaction (HRI), Human-Robot Proxemics (HRP) studies how humans and robots use and manipulate distances between each other with regard to social behaviour and human perceptions. Breazeal [1] has found that humans responded socially to expressive zoomorphic robots in some very fundamental non-verbal ways, including respecting the robot's interpersonal space. Nomura *et al.* [2] found that both participants' negative attitudes and anxiety towards a small size humanoid robot had statistically significant effects on users' preferred (comfortable) robot approach distances. The main aims for our HRP research are to empower domestic or service robots to be able to:

- Detect the presence and position of people in its surroundings
- Approach, pass or avoid people as necessary, while dynamically controlling for socially acceptable HRP distances
- Take account of both the robot's and user's physical situations, and the robot's task context.

The particular HRP distance taken will also depend upon other factors, including each individual human user's preferences, the physical and social situation, and also task context [3]. Some of these other factors which affect HRP are known, but have only been roughly quantified using essentially static measurement methods, such as the HRP framework presented by Walters *et al.* [4]. It is therefore desirable to carry out more comprehensive research to see if some of the richness apparent in human proxemics interactions can also apply to other HRP interactions.

Human Proxemics

In human-human interactions, Hall [5] observed that human social spatial distance varies by the degree of familiarity between interacting humans and the number of participants. Later, Hall [6] provided a framework which categorized the main social spatial zones by interaction and situation. Hall estimated these distances visually but later researchers [7] have assigned numerical values for human-human personal space zones:

- Intimate zone < 0.45m
- Personal zone ≥ 0.45m and < 1.2m
- Social zone ≥ 1.2m and < 3.6m
- Public zone ≥ 3.6m

In the field of human proxemics research, other factors which can also affect proxemic distances between interacting humans have also been proposed. For instance, Stratton *et al.* [8] suggested that uncertainty (or slight perceived threat) can affect human proxemic distances, and makes them take up slightly greater distances from the source of the perceived potential "threat". In a study, for a robot which used different voice styles, participants initially encountering the robot took significantly different comfortable approach distances [9] and it was suggested that these differences may be caused by participants' slight initial uncertainty due to perceived inconsistencies between the robot's appearance and voice styles.

Gillespie and Leffler [10] concluded that much of the observed variation in social distance between communicating humans is accounted for by the relative status of the interactants. Burgoon and Jones [11] explained many seemingly contradictory aspects of human-human proxemic behaviour by suggesting that relatively small (dynamic) manipulations of the distance between participants were a social "reward and punishment" mechanism. This theory can also explain how high status interactors can "reward" lower status interactors by moving closer, but lower status interactors can "reward" higher status interactors by keeping a greater distance.

Human-Robot (HR) Proxemics

Hűttenrauch *et al.* [12] concluded that in HRI user trials most participants kept inter-personal distances from a PeopleBot™ robot corresponding to Hall's Personal spatial zone (0.45m to 1.2m). Previously in HRI trials run using semi-autonomous robot control techniques in HRI trials, we found that children tended to approach a similar robot to similar distances [13] but for individual adults approaching the same robot, the approach distances were more ambivalent and inconclusive [14][15].

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We (Koay *et al.* [16]) also found that people generally allow robots to approach more closely during physical interactions (handing over an object etc.) than for verbal or no interaction conditions. Syrdal *et al.* [17] found people generally prefer more humanoid appearance robots to keep a further distance away than mechanoid appearance robots. Walters *et al.* [18] found that participants' preferences for particular robot attributes (both appearance and height) affected participants' comfortable approach distances with regard to whichever robot type they interacted with. The results from our previous HRP trials [4] are summarized in Table 1, where all distances have been compensated to satisfy a standard measurement between the human and the robot's closest body trunk parts (i.e. not including arms or manipulators). These distance measurements (as best as we can tell from the published details) are also roughly comparable to those made by Hall for his spatial zone distances and also by Stratton *et al.* [8]. Takayama and Pantofaru [19] found that other factors including robot head orientation, gender of participants, and previous experience interacting with both pets and robots also affected peoples comfortable HRP distances.

Factor	**Context(s) – Approach**	**Base Distance = 57cm Estimated Adjustment for Factor (± 0.5cm)**
Attribute or Factor of Robot		
Mechanoid Robot	All – RH All – HR	-3 -7
Humanoid Robot	All – RH All – HR	+3 -1
Verbal Communication	Verbal Interaction – RH	+3
Giving object	Physical Interaction – RH	-7
Taking object	Physical Interaction – RH	-7
Passing	No Interaction – RH	+4
Direction from:	Front – RH Right/Left – RH	+2 -2
Attribute or Factor of Human		
Preferred Robot Humanoid	All Private – RH	-3
Preferred Robot Mechanoid	All – RH	+3
Preferred Height Tall	All – RH	-1
Preferred Height Short	All – RH	+2
Uncertainty or perceived Inconsistency	Initial Encounter – HR	+13
Verbal Communication	Verbal Interaction – HR	+3
Giving object	Physical Interaction – HR	-7
Taking object	Physical Interaction – HR	-7
Passing	No Interaction – HR	+4

Table 1. Factors affecting HR proxemics and corresponding adjustments for Base HRP Distance (57cm) [4]

In order to confirm and extend these findings, investigate whether other factors might apply to HRP interactions, and also effectively measure and quantify any effects, it is necessary to first develop autonomous robot HRP sensing and control capabilities. Haasch *et al.* [28] have presented a mobile companion robot that employs multi modal person tracking, attention mechanism, speech recognition, and dialog manager to interact with a human, but not studied HRP in their work. This paper therefore presents a state-of-art Autonomous Proxemic System (APS) for sensing and control of HRP distance. It discriminates humans from objects, automatically measures the HRP distance, controls for a given desired HRP distance. The robot is also able to follow people around, keeping a desired HRP distance (to the best of the robot’s capabilities, as it moves rather slowly compared to most people). The rest of paper is organized as follows. The next section explains the APS main components and its implementation details. Section 3 describes the experiment that evaluates the performance of APS in keeping the desired HRP distances. Finally, the last section gives a conclusion and prospect of future work.

2. Autonomous Proxemic System

The APS is designed to detect a human in the mobile robot’s surroundings, and enable the robot to approach and keep a desired HRP distance in both static and dynamic states. The APS employs a range of sensors common to mobile robots consisting of a low resolution camera, passive infra-red (IR) sensor, laser, and sonar range finders. It uses computer vision techniques to detect either a face or upper body of a person within its camera range, but also applies a leg detection algorithm to laser range finder data. Meanwhile, it uses infra-red (IR) and sonar sensors to perceive and track human motions and obstacles, respectively. The rest of this section provides more details of how these sensors and associated algorithms are implemented in the APS.

Face Detection

The APS uses face detection to detect and localize people in the focus range of the camera. The main aim of this face detection is to determine whether or not there is actually a human face in the current captured camera frame, and if so return the location. However, face detection is challenging due to variability in scale, location, orientation (up-right, rotated), and pose (frontal, profile). Facial expression, occlusion, and lighting conditions also change the overall appearance of the faces [20].

In our application, we take advantage of an object detector which uses Haar-Like features of an image [21]. This is a refined version of the widely known algorithm created by Viola & Jones [22]. This algorithm is already implemented and trained for face and upper body detection in *OpenCV* [23], the open-source computer vision library adopted for use in the APS. According to a comparative survey in [20], the chosen solution shows a good balance between performance and computational speed. It is also proven that this method is colour independent (i.e., adapt for different skins) and robust to varying light conditions.

Briefly, the chosen face detection algorithm deploys Haar-like features that consist of two or three jointed rectangular regions (Figure 1). The value of a Haar-like feature is the difference between sums of grey level values of pixels within the two rectangular regions.

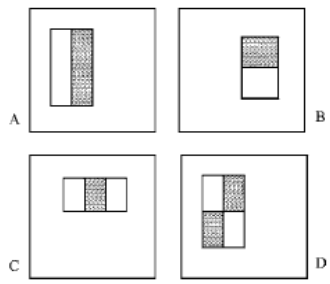

Figure 1. Haar-like features: two or three jointed rectangle regions [22]

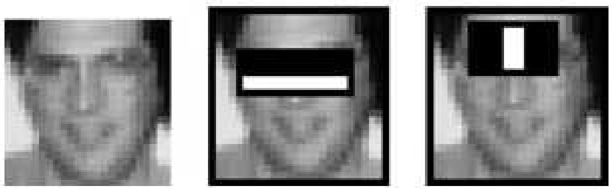

Figure 2. Haar-like features are extracted from sub-windows for face detection [22]

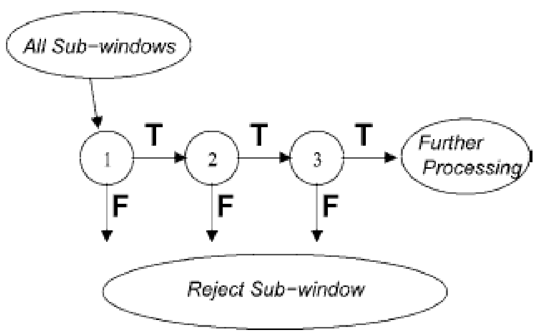

Figure 3. Cascade of simple classifiers applied to the Haar-like features of the sub-windows [22]

Compared with raw pixel values, Haar-like features can reduce in-class, and increase out-class variability, thus making more distinguishable data and easier classification. The Haar-like features are computed from sub-windows of an image (Figure 2). Given an image resolution of 320x240, sub-window resolution of 24x24, and 15 frames per second, the total number of sub-windows with one Haar-Like feature is about 1 million per second which has a relatively large computation cost. To optimize this computation, a cascade of pre-trained simple classifiers (i.e. AdaBoost [21]) with a threshold structure is applied to the features computed from sub-windows. The first classifier eliminates a large number of negative sub-windows and passes almost all positive sub-windows (high false positive rate) with very little processing effort. Subsequent layers eliminate additional negative sub-windows (passed by the first classifier) but which require more computation. After several stages of processing, the number of negative sub-windows has been reduced greatly (Figure 3). Finally, the remaining relatively few sub-windows may contain a face passed as the output of the algorithm.

Bellotto *et al.* [24] presented an adapting regulation for parameters of the face detection method to improve the fast tracking performance in real-time applications. It starts with an image at normal size (320x240) and once it has detected a face (or faces), selects the nearest one, and then scans just a sub-image containing the selected face. Meanwhile, it reduces the sub-windows size into 80% of the selected face size. This significantly increases the detection speed (~4 times) and keeps track of one face as long as it can be detected.

The proposed algorithm [23] is capable to be extended to distinguish different visual patterns. Then, as mentioned, we have extended the visual object detection to detect upper body rather than the exclusive face detection. Moreover, we deployed the face detection classifier with different profiles. By this means, the robot can perceive people even when it is behind or to the side of the person. More details about the implementation are discussed in the next sub-section. To supplement the face detection system, additional sensing tools are required to detect humans in the surrounding area. This is because the applied face detection is limited in both performance (false positives, negatives and lost targets) and the area of scanning coverage.

Leg Detection

Leg detection is a pattern recognition terminology that can discriminate and localize people legs using laser readings [29]. The leg detection system processes the range data collected by laser, extracts the edges produces by the objects, and localizes the patterns of edges that match with the human leg patterns'. Although, the detected patterns are not guaranteed to belong to human legs, they provide potential directions to explore to confirm whether people are in the environment. In APS, leg detection is employed to provide the turning direction for the robot when no one was detected by the visual detection object.

The laser sensor provides range data from 180° covering the front and sides of the robot, at a height of about forty centimetres from the floor, and with half degree resolution. The scanning area is semicircular with a radius of 8 meters. The laser range data, according to the manufacturer's specifications, are very accurate with errors of a few millimetres. Figure 4 depicts a snapshot of the range data in the presence of a person in the scanning area.

Belletto *et al.* [24] [25] presented a novel detection algorithm to find human legs by using laser scans. It is designed to work either in large empty environments or small cluttered rooms, and is able to distinguish among different leg postures, thus improving the discrimination of false positives. The leg detection algorithm extracts the necessary features (edges produced by the objects) from a single laser scan, and identifies typical patterns (relative to particular leg postures) that, in most of the cases, are distinguishable from the other objects in the environment. The desired leg patterns, shown schematically in Figure 5, correspond to three typical situations: two legs-apart (LA), forward straddle (FS), and two legs-together or SL. The first pattern is usually very common when a person is standing in front of the robot. The second is most likely to happen when the person is walking. The last pattern covers most of the remaining postures. However, it can also be generated by other objects in the environment, giving rise to false positive detections [25].

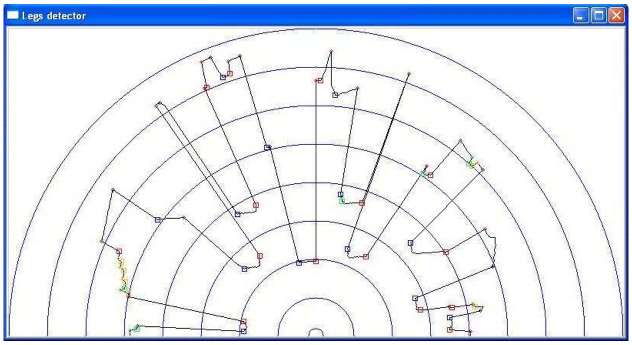

Figure. 4. Range data collected from the laser sensor with marked edges

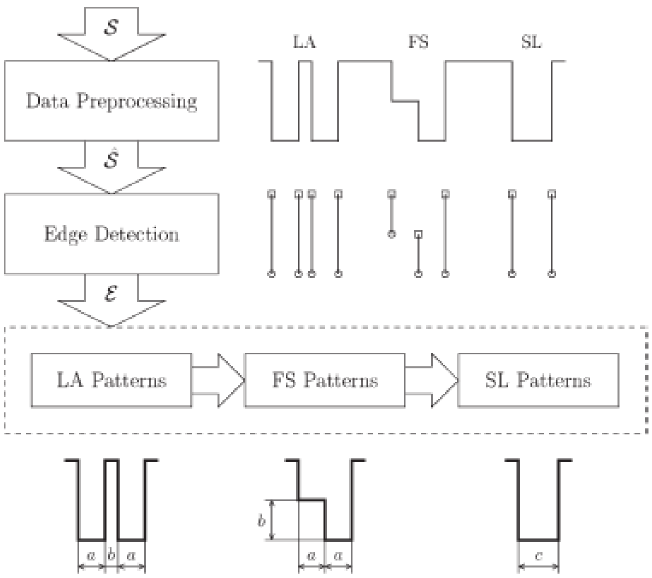

Figure 5. Leg patterns and the Leg Detector's schematic diagram [25]

As shown in the schematic presentation of Figure 5, the algorithm is divided into three main parts: data pre-processing, detection of vertical edges, and finally extraction of leg patterns. The laser range data are pre-processed by applying a local minimization operator to remove possible spikes due to reflections on sloped surfaces, and a local maximization operator to discard thin objects such as table legs. Suppose the angular step between two consecutive laser scans is constant, and the range data after pre-processing is stored in an array $S = [r_1 \ldots r_i \ldots r_M]$, where r_i is the range measured on the direction θ_i, and M is the total number of readings. If we represent S on a Cartesian graph, we can identify a sequence of vertical edges defined as follows. The doublet $\{r_i, r_{i+1}\}$ can be considered an almost vertical edge if the distance $|r_{i+1}-r_i|$ is greater than a given threshold. Moreover, we can distinguish a left edge, when $r_i>r_{i+1}$ from a right edge, when $r_i<r_{i+1}$, and refer to them as L_i and R_i, respectively.

The resulting vertical edges are initially queued into a list $E = \{e_1 \ldots e_n \ldots\}$, where each element e_n can be either an L or R edge. If they are very close and almost aligned, adjacent edges of the same type are connected to form a longer one. After that, from the updated list of connected edges, we extract all the subsets that might belong to one of the three leg patterns described before. The order of patterns that we look for is as follows.

- The LA pattern is a quadruplet {L, R, L, R}.
- The FS pattern is a triplet {L, L, R} or {L, R, R}.
- The SL pattern is a doublet {L, R}.

Every edge is removed from E as soon as it contributes to form one of the aforementioned sequences. Therefore, all the LA patterns, which are normally the most reliable, are extracted first, while the SL patterns, which are the easiest to misinterpret, are left at the end. During the search for the patterns we consider some constraints and spatial relations between edges, including maximum normal distance between legs and limits on their size. With reference to Figure 5, some dimensional constraints are fixed for the measures a, b, and c, which are, respectively, the leg's width, the maximum step length, and the width of two legs together. These are used by the algorithm's procedures to recognize LA, FS, and SL patterns. Finally, the distance and direction of the detected legs are calculated from the midpoint of each pattern [25].

Motion Detection

Many objects normally emit IR radiation, invisible to human eyes that can be detected by electronic devices designed for such a purpose. The APS motion detector is designed to perceive a human as the robot is moving. It is based on a passive IR sensor, which is an electronic device that measures IR light radiating from objects in its field of view. It is a passive sensor, which means that it does not emit an IR beam but merely passively accepts incoming IR radiations. Intensity of the emitted radiation is proportional to the objects' temperature [26], and apparent motion is detected when an IR source with one temperature, such as a human, passes in front of an IR source with another temperature (e.g. a wall etc.). Furthermore, a motion can also be realized when an IR sensor moves relative to an IR source with one temperature, such as a human, standing in front of an IR source with another temperature. This feature can be adopted to detect the positional change between a human and a mobile robot carrying the IR sensor.

In our application, we set up an IR sensor connected to an analogue to digital converter (ADC, Phidget Interface Board) on top of the mobile robot to perceive the presence of a human in its surroundings. The sensor was fixed at a height approximately 1.2 meters from the floor to read IR radiations emitted from the human body (i.e. trunk) and avoid typical non-human IR sources (e.g. heating radiators) in a room. The sampling frequency was 5Hz, and the recorded data was passed through a low-pass filter to remove noises produced by the vibration. The gradient of the filtered data represents a change in successive IT radiation measurements and indicates a motion when it exceeds a certain threshold. The threshold was chosen after preliminary tests, and adjusted to detect the motions produced by a human within a range of 5 metres.

According to the desired scenarios in our application, we deliberately ignored any fast or weak motions from the passive IR sensor by adjusting the sampling rate, low-pass filter and threshold parameters. After tuning, the robot detected the presence of a static human when the robot passes by, or when a human moves in front of the robot.

System Implementation

The APS is a real-time controller developed for the Pioneer PeopleBot™ robot. It has a modular design and employs the above-mentioned detectors as modules running in multi-thread mode. The APS is implemented in C++ using ARIA and OpenCV libraries. It runs on a Dual Core PC (with Windows XP) connected directly to the robot via the USB serial port adaptor.

The APS includes both control and sensing functions. The controlling commands are made up of 'Turning Left/Right' and 'Moving Forward/Backward', both implemented as Actions in ARIA. The Turning command has a priority over Moving; this means the robot first turns toward the person and then starts approaching. The Moving command checks regularly the range devices (i.e. Sonar and Laser) to keep the HRP distance and avoid obstacles. The cycle time of the robot controller, at which the sensors and commands are regularly updated, was set to 200ms. This is a sensible rate for a companion robot in normal daily activities.

APS sensing functions include face and upper body detection, leg detection, and motion detection using the camera, laser, and Infra-Red (IR) sensor, respectively. Moreover, the obstacle avoidance Action also uses the sonar and laser range data. APS gives a higher priority to the camera-based functions over the laser [30]. This means APS manipulates the robot using vision-based information, as long as it detects a face or an upper body in view of the camera. When a face or an upper body is detected, APS uses its relative horizontal location in the image to adjust the robot's bearing angle towards the human. In the absence of a detected human by the camera system during a limited time, APS then uses the information provided by the leg detector to manipulate the robot. Motion detection, due to its particular characteristics, just stops the robot turning (i.e., interrupt the Turning command) when it spots a human in its range.

To make a sensible integration of the detectors, we require considering their features along with the characteristics of the controller. The laser-based leg detector is very accurate and in most of the cases is much more reliable than face detection [25]. Moreover, the computational time needed by the leg detector is much less than that one required by the face detection module. Considering the modules running asynchronously in real-time operation, the face and leg detection processes take about 500 and 250msec, respectively. The range covered by the laser device is much wider than the camera view. While the laser covers a semicircular area with a radius of 8 metres, the camera view is limited to approximately 40°. As mentioned, the face detection is featured to discriminate faces with different profiles as well as the upper body. However, even if the camera is fixed at about 1.4m from the floor (which is about a normal person's face height), there are cases when a face or upper body cannot be detected because a person is too tall, too short, or very close to the robot.

3. Experiments and Results

According to Section 1, a domestic robot should be able to keep an acceptable HR proxemic distance during interaction with a human. The APS is supposed to manipulate the robot in such a way that it keeps reliably the desired HRP distances corresponding to different settings. We conducted an experiment, to evaluate the performance in HR proxemic control produced by APS.

Desired distance in APS									
	450	550	650	750	850	950	1050	1150	1250
Recorded distances for subject 1									
1	385	500	595	725	715	885	1015	1055	1055
2	395	495	645	730	825	885	1005	1005	1125
3	395	485	635	735	735	825	960	1065	1115
4	405	475	620	705	765	845	1015	1015	1135
5	385	505	595	675	755	865	985	1055	1145
Recorded distances for subject 2									
1	365	540	560	650	760	820	895	1005	1085
2	375	450	570	650	760	830	885	1005	1105
3	355	480	570	660	750	825	915	995	1095
4	345	480	565	655	755	835	895	985	1105
5	335	480	575	665	765	825	925	1005	1115

Table 2. Recorded HRP distances corresponding to different settings (in millimeters)

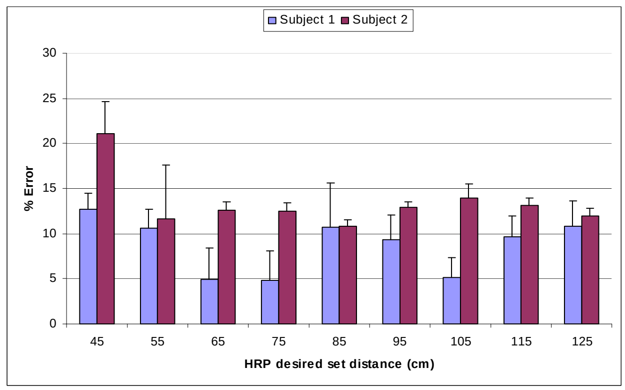

Figure 6. Error (%) of raw HRP distances

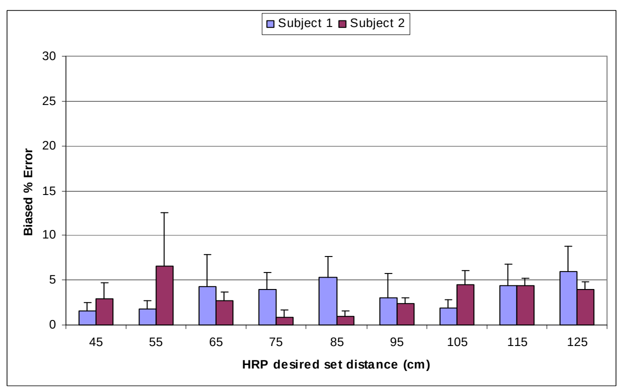

Figure 7. Error (%) of HRP distances after applying bias values (6cm for Subject 1 and 10cm for Subject 2)

To have a realistic evaluation, the experiment with two participants was conducted in a real living room with usual furniture in the University of Hertfordshire 'Robot House'. The 'Robot house' is a house near the University, based in a domestic area, which appears to be like any typical UK house, but has been adapted so that HRI experiments and user trials can be performed in an ecologically valid, real home environment, rather than a laboratory or simulated home surroundings. In the experiment, we measured directly using a tape measure the actual distance between static human and robot corresponding to different desired HRP values set in APS. The experiment was designed to evaluate the reliability and repeatability of the APS performance; Hence, we repeated five trials for each setting, and also recorded the error. The error refers to the difference between desired and actual HRP distances. Some error is inevitable, since the APS records the nearest distances read by the sonar and laser at a fixed height (i.e. 0.3 and 1.2m for sonar and 0.4m for laser) from the floor as HRP, while we measured the actual distance at a height that includes the closest point between human and robot's trunks. However, it was expected to record errors with constant bias and low variance. The bias mainly depends on particular subjects' body shape.

The experiment examined HRP settings from 45 to 125 centimetres, and repeated trials for each setting five times. Table 2 demonstrates the recorded distances for two participants and nine settings. Figures 6 and 7 illustrate the mean and standard deviation for error of HRP distances for each subject and setting. The former is for the raw data and the later depicts the error rate after subtracting the bias value to reduce the constant part of the error.

The bias is a constant value that exists in the differences between measured values by the human and robot. It is primarily caused by the difference in the height of the point of measurement. The bias value therefore depends mostly on individual humans' body shapes and is worked out for each subject. Considering the errors with normal distribution, it can be calculated using the '*three-sigma*' rule in Statistics [27]. The bias is worked out by subtracting the one-third of the standard deviation (STD) of the recorded errors from the absolute value of their mean. It was found to be 60 and 100 millimetres for Subject 1 and 2, respectively.

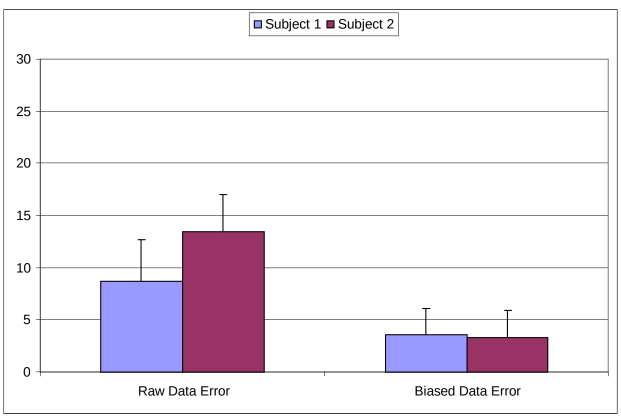

Figure 8. Error (%) decreases significantly by applying the bias values to raw HRP distances

Figure 8 shows that applying the individual subjects' biases to the raw HRP distances from the APS, increased significantly the accuracy of measurement. The adjusted (biased) mean HRP error is about ±1.5% with repeatability of ±1%. This implies an approximate error of ±0.75cm in HRP distance measurements close to the 57cm base distance [4] from the Proxemic Framework from Table 1. This is acceptable for our future work which will focus on HRP interactions within the near Personal Zone distances (40 – 100cm). We hope to refine the measurement accuracy in the light of more data from a wider range and number of participants in future trials. We also intend to improve the APS in future work by incorporating a learning mechanism that can learn users' proxemic preferences and individual HRP parameters during run-time.

4. Conclusion

The social behaviour of a mobile robot can make it socially acceptable and effective as a companion. In HRI, the study of how human and robot use and manipulate distances between each other with regard to social behaviour and perceptions is called human-robot proxemics (HRP). An aim of HRP research is that a social service robot should be able to detect presence of people in its surrounding and approach them to an acceptable proxemic distance. The particular HRP distance depends on individual humans' preferences, the robot's task and services, social and physical situation, and possibly other factors. In this paper we proposed an autonomous proxemics system for a mobile robot. Experimental findings indicate that the proposed system works reliably and keeps a desired HRP distance with a total error variance about ±1.5%. We intend to improve the APS in future work by refining the HR measurements and incorporating a learning mechanism that automatically can adapt to individual users' HRP preferences and parameters.

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