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A Multi-Modal Feedback Communication Interface for Human Working Posture Adjustments

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Abstract. This paper studies non-physical feedback mechanisms to guide human workers toward ergonomic body postures. Specifically, the focus is to solve the tasks that involve no direct physical interaction between the human and the robotic system, therefore tactile guidance by the robot body is not feasible. We propose a multi-modal ergonomic posture guidance system that comprises visual feedback and speech-based audio feedback. We hypothesise that the proposed multi-modal system leads to better performance compared to uni-modal feedback systems when trying to guide users from one pose to another. To test the hypothesis we conducted an experiment that compared conditions with only audio feedback, only visual feedback and multi-modal feedback. In addition, we examined speech-based audio guidance in joint space and in endpoint space. The results showed that the speech-based feedback in joint space came out as the preferred audio feedback due to its ability to allow users to carry out efficient and coordinated inter-joint movements, especially in cases of high redundancy. Furthermore, the proposed multi-modal feedback system was superior compared to the other feedback modalities both in terms of objective measures and subjective measures.

Keywords: Human-machine interaction · Ergonomics · Visual feedback · Audio feedback · Human factors

1 Introduction

The manufacturing industry is one of the key components of modern society. Much of the production process can be automated by robots, such as mechanical arms and non-mechanical smart systems, to improve the production speed and quality of products. Nevertheless, human workers are in many cases still an essential part of the production process due to their superior cognitive capabilities and adaptability. Unlike robots that can perform demanding tasks uninterrupted for prolonged periods of time, human workers are susceptible to cognitive and physical stress caused by various working conditions, such as unsuitable working style [6] or excessive forces on the body [11]. The continuous presence of such physical stress can lead to a dramatic increase in work-related musculoskeletal disorders (WMSD) [2,23].

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When humans are working in robotised environments, we can exploit smart robotic systems to account for human ergonomics and work-related musculoskeletal risks. These aspects can be monitored by using predefined ad-hoc tables like RULA and REBA [4,7,15,24] or biomechanical models [1,10,16,18]. When the robotic system detects ergonomic risks in the existing working configuration, it can alert the human worker to reconfigure the body posture online through different types of feedback. For example, the approaches [10,18,19,26] used collaborative robotic arms to reconfigure the human co-worker's body into a more ergonomic pose through physical interaction. Similarly, force feedback through haptic interfaces are used to constrain [22] or reconfigure [17] human operator's arm in teleoperation. Nevertheless, not all manufacturing tasks involve physical human-robot interaction or mechanical robotic systems. In such cases, other feedback modalities have to be employed to alert the human co-worker about ergonomic risks during the production process. For instance, wearable vibrotactile devices can be used to alert and guide the human joints to a more ergonomic posture [9]. However, wearable devices can be time-consuming to equip and may irritate the workers with vibrations.

Alternatively, contactless and non-tactile feedback can be provided in a visual or audio form by a smart system (i.e., a non-mechanical robot). For example, the method in [14] used an external camera to track the human body posture and display excessive joint torques to the worker on a monitor in real-time. To a similar end, audio feedback can be used to guide the human posture [13,21]. The study in [20] developed a visual interface to map the shared human-robot workspace in 3D based on multiple ergonomic metrics. The work in [27] exploited latent space to generate a 2D map that can encode a complex multi-degree of freedom (DoF) information about the body. However unimodal visual or audio systems each have their limitations. Visual feedback systems require human workers to look at the monitor, which can draw attention away from the actual task. In addition, small but critical posture corrections might not be easily visible to the user. On the other hand, by using audio feedback the human worker does not need to look away from the actual task. Nevertheless, the transmission of complex multidimensional data for pose correction (e.g., name of the joint, direction of movement and magnitude of movement, etc.) through audio techniques is typically slow and can easily overwhelm or confuse the user. Furthermore, audio feedback systems can suffer from problems of habituation, where a continuous presence of sound can get obscured in the background and the user realises this only when the audio feedback either stops or changes [3].

The solution to these limitations is to combine visual feedback and audio feedback into a multi-modal system. Visual feedback offers a fast guidance method for large posture corrections since the human worker can see the actual posture with respect to the desired one in real-time. On the other hand, audio feedback can be used to guide humans for minor pose adjustments once the pose is already close enough to the desired one, or when the actual task requires the full visual attention of the worker. There is plenty of existing literature that has already shown that multi-modal feedback improves motor coordination and learning in humans [25]. Nevertheless, a similar study for methods related to body posture adjustments to improve human worker ergonomics is still missing.

In order to address this, we developed a multi-modal ergonomic guidance system to combine the advantages of visual and audio feedback and hypothesis that *the multi-modal system will lead to better performance compared to either visual feedback modality or audio feedback modality when trying to guide the human users from one pose to another*. To test the hypothesis we conducted an experimental study to compare the three contactless guidance methods: audio-only feedback, visual-only feedback and multi-modal feedback.

2 Methods

2.1 Feedback Mechanism Design

We designed four types of feedback mechanisms in order to carry out a comparative study and test our hypothesis. We examined two speech-based audio feedback methods; one acting in joint space and the other acting in endpoint space. We designed a visual feedback method that can display the current human body posture with respect to the desired one. Finally, we designed a multi-modal feedback method that combines audio and visual feedback modalities.

Audio Feedback in Joint Space Speech-based audio feedback in joint space involves a feedback method where the user adjusts the body posture in a joint-specific manner through verbal commands. The commands were limited to the shoulder and elbow joints for this study. The wrist was not considered since it has less impact on the arm's dynamics, compared to the shoulder and elbow. The commands were in the English language and were output at a rate of 180 words per minute, which is slightly higher than the average of 140–160 words per minute worldwide. The reason for this was to increase the bandwidth and at the same time retain the understandability. The direction and magnitude of the movement were given relative to the current angular position of the joints. The commands were given sequentially for each joint with a short pause in-between. Further corrective commands were given after the user made the movement based on the previous commands and temporarily maintained the arm configuration. Once the user oriented his/her joints in the desired pose (which would be required to perform tasks such as drilling/polishing), the system alerted the user by producing a beeping sound. Table 1 shows the list of commands the user received for this particular modality.

Table 1. List of speech-based audio commands for joint space feedback

Command	Joint	Meaning
"Move arm up by xx degrees"	Shoulder	Shoulder flexion
"Move arm down by xx degrees"	Shoulder	Shoulder extension
"Flex elbow by xx degrees"	Elbow	Elbow flexion
"Extend elbow by xx degrees"	Elbow	Elbow extension

Audio Feedback in Endpoint Space Another speech-based audio feedback mechanism was created which provided verbal commands for endpoint movements in Cartesian space. The wrist joint was assumed to be the endpoint of our study. The commands were in the English language and were output at 180 words per minute. The direction and magnitude of the movement were relative to the current position of the endpoint and the unit of movement was in centimeters. Table 2) shows the list of commands the user received for this particular modality.

Table 2. List of speech-based audio commands for endpoint space feedback

Command	Meaning
"Move arm back by xx"	Move EP towards the body
"Move arm forward by xx"	Move EP away from body
"Move arm down by xx"	Move EP vertically down
"Move arm up by xx"	Move EP vertically up

Visual Feedback The visual feedback system was assumed to be the benchmark in the comparison study because of several reasons. First, concurrent visual feedback is the easiest and the most natural form of feedback modality [25]. Second, visual feedback is superior to other senses when it comes to understanding spatial information [25]. Third, humans usually rely on visual feedback when it comes to following trajectories and interacting with the environment [5]. For providing visual feedback to the user we developed a graphical user interface (GUI) in OpenCV (see Fig. 1). GUI was based on a monitor that presented a graphical representation of the human body (red) and the target pose (white) in real-time. The user had to reach the desired target pose by monitoring GUI, and when it was reached the colour of the screen changed to green.

Multi-Modal Feedback The multi-modal system interactively combines the two modalities of visual feedback and speech-based audio feedback in joint space. The proposed system exploits the advantages of both visual and audio systems. The initial larger pose adjustments can be done by relying on visual feedback. Then, when the body is close enough to the desired pose (± 5 degrees), the final adjustment can be done completely based on the audio feedback. This way the users do not have to constantly look up at the GUI to receive visual feedback about their pose. Instead, they can concentrate on the actual task (e.g., performing drilling/polishing with a tool at the endpoint) while listening to the audio feedback for minor adjustments. The users can still switch to visual feedback at any time if larger corrections are required or when looking at the task is not so important.

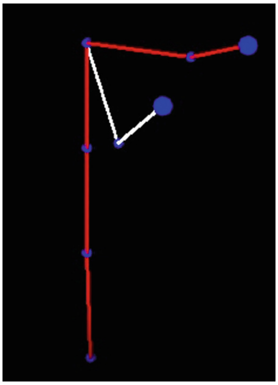

Fig. 1. Graphical user interface of the visual feedback system. The current pose of the user is shown in red and the desired pose is shown in white. The blue circles represent the five major joints of the human body that we considered in this study: ankle, knee, hip, shoulder and elbow. The larger blue circle at the end represents the wrist, which is the endpoint.

2.2 Experimental Design

The study included 14 participants (10 male, 4 female) between 23 and 27 years old (25.14±0.99 years[1]) who were all proficient in the English language. Exclusion criteria were movement, vision and/or hearing impairments. The participants gave informed consent prior to the study. The study was approved by TU Delft Human Research Ethics Committee.

A within-subject experiment was conducted to compare the user performance in three conditions: *audio-only feedback*, *visual-only feedback* and *multi-modal feedback*. The performances for the audio and multi-modal feedback were compared against the visual feedback, which we used as a benchmark. The user performance was evaluated by both objective and subjective measures. An additional experiment was conducted to compare audio feedback acting in joint space to audio feedback acting in endpoint space (see Sect. 5).

Objective Measures

- **Task Completion Time** (TCT) measures the time to complete the pose adjustment, which was defined from start time until the time when a user holds the desired pose for 10 s. A smaller TCT indicates a better performance as it implies that the feedback helped the user to complete the task quicker (See Fig. 2).
- **Total Distance Moved** (TDM) refers to the sum of integrated joint angular movements that are required for the user to successfully orient both joints (shoulder and elbow) within the threshold (±5 degrees) of the desired angular position and any movements while staying inside the threshold for 10 s. A larger TDM indicates

[1] This format of reporting values corresponds to mean±standard deviation and applies for the rest of the paper.

worse performance as it implies that the feedback was not efficient and therefore the user made multiple pose adjustments (e.g., overshoots and undershoots) before reaching the desired pose.(See Fig. 2)

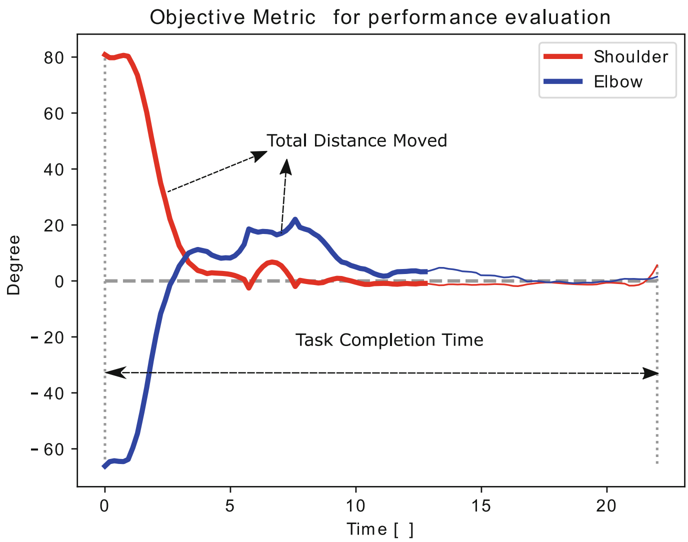

Fig. 2. An example of a pose reconfiguration task with highlighted Task Completion Time (TCT) and Total Distance Moved (TDM) measured. For clarity in this example, the final pose angles have been subtracted from both joints so that they converge to zero.

Subjective Measures

- **NASA-TLX** is a subjective measure used to evaluate the overall workload by calculating a weighted average of 6 different measures: mental demand, physical demand, temporal demand, performance, effort and frustration [8]. A low score indicates that the user-perceived low workload in pose reconfiguration by using a given feedback method.
- **van der Laan** is a subjective questionnaire used to evaluate the acceptability of a given method with usefulness and satisfaction scores [12]. Each score ranges between -2 to +2. The final score can be plotted on a 2D graph, where usefulness is on the x-axis and satisfaction is on the y-axis. The point in the upper right quadrant of the graph indicates good user acceptability.

In the main experiment, the participants underwent 5 trials for each of the three conditions (i.e., audio, visual and multi-modal). The order of the conditions was randomised among the participants. Note that there were two audio conditions (see Sec. 5 for details). To familiarise with the feedback mechanisms and to minimise the learning effect, each subject underwent two or more practice trials before the experiments.

The participants were asked to stand next to a camera system which was responsible for capturing their body posture in real-time. All angular measurements were done in the sagittal plane for the right side of the body. Different starting and ending poses were selected for the 5 repetition trials in each condition. The participants were then asked to follow the feedback commands and to reach the desired pose. Their main objective was to try and complete the reconfiguration as quickly as possible but at the same time avoid unnecessary position errors. After finishing the 5 trials for each condition, the participants were asked to fill in the NASA-TLX and van der Laan questionnaires.

The results of the experiment were compared through a two-tailed Student's t-test to check for statistical significance between the conditions. The level of significance was set to 0.05.

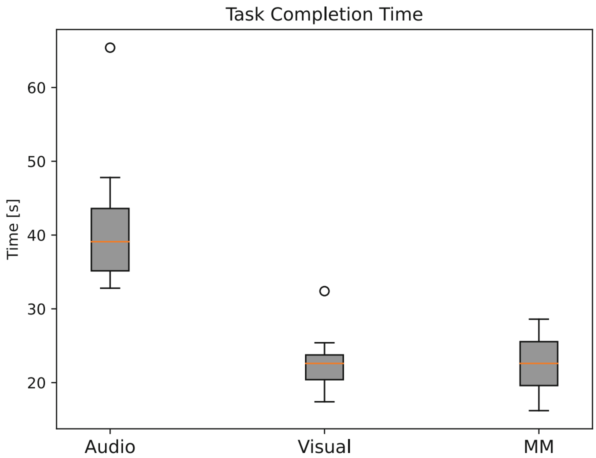

Fig. 3. Box-plots of time to complete the reconfiguration for each condition.

3 Results

3.1 Task Completion Time

Results of TCT comparison are shown in Fig. 3. Audio feedback had the highest TCT (40.97±8.04 s) when compared to visual feedback (22.49±3.62 s). The difference was statistically significant ($p < 0.05$). On the other hand, multi-modal (MM) feedback had a similar task completion time as visual feedback (22.29±3.86 s). The difference was statistically insignificant ($p = 0.89$). The overview of all measures is in Table 3.

3.2 Total Distance Moved

Results of TDM comparison are shown in Fig. 4. Audio feedback had a higher overall movement of the shoulder (134.53±42.46 degrees) and elbow (172.31±54.80 degrees)

Table 3. Table shows the mean results for the objective and subjective metrics.

Metric	Audio	Visual	Multi-modal
Task Completion Time (seconds)	40.97*	22.48	22.28
Total Distance Travelled (degrees)	Shoulder = 134.53*	Shoulder = 108.39	Shoulder = 119.62*
	Elbow = 172.31*	Elbow = 106.31	Elbow = 119.51
NASA - TLX Workload Index	42.16	41.49	28.99*
Van der Laan	Usefulness = 1.27	Usefulness = 1.15	Usefulness = 1.54
	Satisfaction = 0.66	Satisfaction = 1.03	Satisfaction = 1.28

Audio and multi-modal systems are individually compared to the visual system with a two-tailed Student's t-test to check for statistical significance. The values highlighted by * indicate $p < 0.05$.

when compared to visual feedback for the shoulder (108.396±7.85 degrees) and elbow (106.42±14.86 degrees). The differences were statistically significant ($p < 0.05$ for both joints). On the other hand, multi-modal feedback had a slightly larger overall movement for both shoulder (119.63±16.34 degrees) and elbow (119.51±24.21) when compared to visual feedback. The difference was statistically significant for shoulder ($p < 0.05$) and insignificant for elbow ($p = 0.10$)

3.3 Subjective Measures

Results of subjective analysis are shown in Fig. 5. Audio feedback had an average overall workload index of 42.16 and visual feedback of 41.50, making both feedbacks almost equally demanding. There was no significant difference ($p = 0.90$). Multi-modal feedback had an average overall workload index of 29.00, which is significantly lower as compared to visual feedback (p<0.05).

According to the van der Laan questionnaire, multi-modal feedback was deemed to be the most acceptable by the participants and it achieved higher scores on both usefulness and satisfaction scales (see the top-right graph in Fig. 5).

We also asked the participants to rank the systems between 1-3 (1 being the best and 3 being the worst) based on their preference to further corroborate the results of the subjective measures. The multi-modal feedback system stood out to be the clear favourite with 9 out of 14 participants voting it to be their preferred form of feedback for pose guidance.

4 Discussion

4.1 Task Completion Time

Audio feedback had on average the highest task completion time among the three methods. This can be attributed to the low information transmission bandwidth of a speech-based format. The participants had to wait and listen to the entire command before could

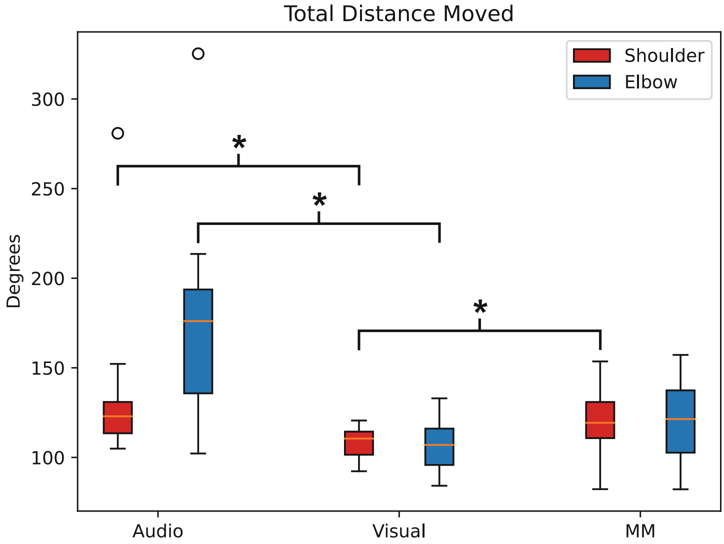

Fig. 4. Box-plots of total distance moved by the individual joints during the reconfiguration for each condition. Statistical significance is indicated by *.

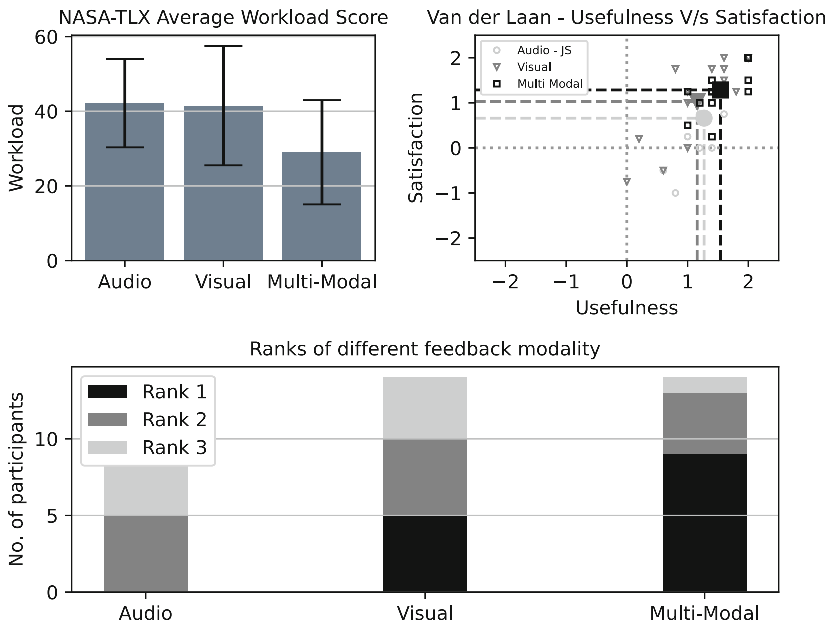

Fig. 5. Results of subjective measures: NASA-TLX (top-left), van der Laan (top-right) and preference (bottom)

they carry out the pose adjustments. In addition, unlike using visual feedback, they did not know how far or close they were to the desired pose, which led to overshooting or undershooting of the target pose. On the other hand, visual feedback allowed the participants to be aware of their current pose with respect to the desired pose. This in general prevented overshooting or undershooting of the desired pose and thus reduced TCT.

Multi-modal feedback had a similar TCT compared to visual feedback, even though the participants had to switch from one modality to another during the pose reconfiguration. The participants relied on visual feedback to carry out larger movements since they could visualise the difference between the current pose and the desired pose, making them move more quicker. Audio feedback was activated only when the participant was ± 5 degrees away from the desired position, thus limiting the comparatively slower audio feedback to only a small portion of the task. The proposed multi-modal system, therefore, achieved the benchmark performance in terms of TCT.

4.2 Total Distance Moved

Audio-based feedback had a significantly larger distance travelled for both the shoulder and the elbow when compared to visual feedback. This can also be attributed to the participants not knowing how far or close they were to the desired pose, which led to overshooting or undershooting of the target pose. Further adjustments for overshoots or undershoots accounted for extra movements that lead to an overall higher TDM. By using visual feedback, the current pose with respect to the target pose is clear at all times and therefore overshoots or undershoots can be minimised.

Multi-modal feedback had slightly larger overall movements for both joints when compared to visual feedback. In the case of multi-modal feedback, the audio modality was activated only when the participant was within ± 5 degrees from the desired position. The additional adjustments during the audio mode could account for the slightly larger TDM. Still, this might be an acceptable tradeoff when visual attention should be given entirely to the actual task of the worker. For example, if the worker should weld or polish a part held by a robot, he/she should visually pay attention to the welding action rather than to the visual feedback related to ergonomics.

Another interesting aspect that can be seen in Fig. 4 is that on average the participants moved their elbows more than their shoulders in the case of audio feedback. This could potentially be attributed to several reasons. Since the elbow constitutes a connection between the shoulder and the hand (arm endpoint), the participants might have unintentionally changed the elbow while changing the shoulder position. Thus, when the users moved the shoulder by the commanded amount, they also moved the elbow for a small amount without having received any command regarding the elbow movement. This would naturally lead to more subsequent corrections of the elbow.

The above-mentioned problem is not present for either multi-modal or visual feedback. This could be because in both these conditions the participants relied more on visual feedback, which would make them quickly aware of any such unintentional movements.

4.3 NASA-TLX

The participants deemed audio feedback and visual feedback to be almost equally demanding. The perceived high workload for audio feedback can be attributed to not seeing the current pose with respect to the target pose, and therefore having to make more adjustments. In addition, constant audio feedback might have been perceived somewhat as an annoyance by the participants. The perceived high workload for visual feedback can be attributed to participants having to constantly pay attention to the GUI while carrying out the task.

The participants deemed multi-modal feedback to be significantly less demanding as compared to the other two. This could be attributed to the method exploiting the advantages of both audio feedback and visual feedback. On one hand, the participants could visually check for the current pose with respect to the target pose at any time. On the other hand, they no longer had to constantly look at the GUI, but could switch to audio feedback and concentrate on the task after reaching a pose close enough to the target pose.

4.4 Van der Laan

All feedback modalities are in the upper right quadrant, which indicates that they are acceptable to the participants. However multi-modal feedback was indicated to be more useful and satisfying as compared to the other two. The usefulness could be higher given that it helped to redistribute the mental workload by allowing participants to concentrate more on the task rather than the feedback, unlike in the case of only visual feedback where the participants could either concentrate on the task or on the feedback. The satisfaction rating was the highest most likely because the system presented audio feedback only when participants were close enough to the desired pose and not throughout the trial, which was the case for the only audio feedback and might have caused annoyance.

5 Supplementary Experiment

The goal of the supplementary experiment was to motivate our choice of using speech-based audio feedback acting in joint space instead of in endpoint space when designing the multi-modal feedback system. We compared the user performance between audio feedback in joint space and audio feedback in endpoint space using the same metrics as mentioned in Sect. 2.2. The same group of participants performed the experiments under these two different audio feedback conditions in order to experience both. The order in which the conditions were presented to the participants was randomised.

5.1 Results

Audio feedback in endpoint space (29.41±3.83 s) had a significantly lower ($p < 0.05$) TCT as compared to joint space feedback (40.97±8.04 s).

Shoulder (shoulder = 126.66±34.13 degrees) and elbow (161.17±64.38 degrees) TDM for endpoint space feedback were slightly lower as compared to shoulder

(134.53±42.46 degrees) and elbow (172.32±54.80 degrees) TDM for joint space feedback. However, there was no significant difference ($p = 0.6$) between either joint in either condition.

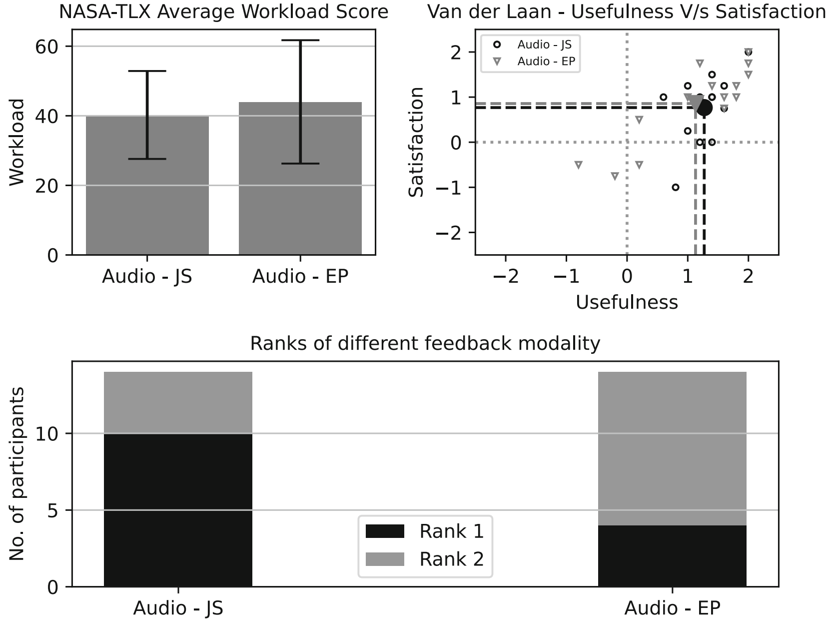

Fig. 6. Results of subjective measures comparing audio feedback acting in joint space and in endpoint space.

The results of subjective evaluation are shown in Fig. 6. Audio feedback in joint space had an overall workload index of 40.24 as compared to 44.00 for endpoint space feedback. The difference was not statistically significant ($p = 0.53$). The results of the van der Laan questionnaire show that the scores for both feedback methods lie in the upper right quadrant (top-left graph in Fig. 6), making them acceptable to the participants. Additionally, we also asked the participants to rank their preferred feedback mechanism to further corroborate the results of the subjective questionnaires. Surprisingly, 10 out of 14 participants preferred the audio commands in joint space (bottom graph in Fig. 6).

5.2 Selection Justification

According to the result, the participants generally took significantly less time to complete the reconfiguration in endpoint space as compared to joint space. In addition, they had an overall slightly less movement of either joint in endpoint space as compared to joint space. On the other hand, subjective scores for workload and acceptability were

Table 4. Table shows the mean results for the objective and subjective metrics.

Metric	Joint Space	EndPoint Space
TCT (seconds)	40.97*	29.41*
TDM (degrees)	Shoulder = 134.53	Shoulder = 126.66
	Elbow = 172.31	Elbow = 161.17
NASA-TLX	40.24	44.0
Van der Laan	Usefulness = 1.27	Usefulness = 1.13
	Satisfaction = 0.77	Satisfaction = 0.86

The results of the audio feedback systems in joint space and endpoint space are compared through Student's t-test to check for statistical significance. The values highlighted by * indicate $p < 0.05$.

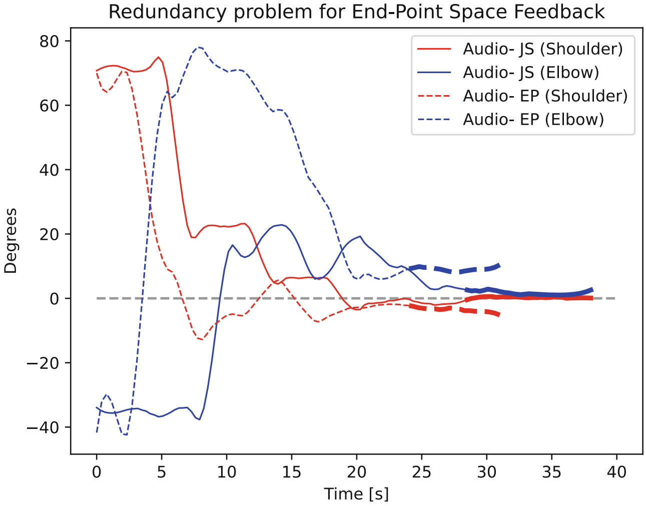

Fig. 7. Demonstration of redundancy problem while using audio feedback in the endpoint. The highlighted portion indicates the last 10 s of the trial where the participant was asked to hold after having reached the desired joint or endpoint positions. By using feedback in joint space, the participant was able to converge his joints to the desired ergonomic pose, whereas by using feedback joint space, the participant is far away from the desired joint positions even though the endpoint (wrist) has successfully reached its desired position.

similar. However, most participants preferred to work with feedback in joint space over endpoint space.

While the evaluation results are generally favourable for the endpoint space method, it has one major conceptual limitation; it cannot be used in cases where there are redundant joint degrees of freedom. The endpoint feedback only gives commands for the positioning of the endpoint and disregards the individual joint positions, therefore the user can orient their joints in multiple ways to reach the same endpoint position (See Fig. 7). This cannot ensure that the user will select an ergonomic configuration among many options, which is the main application of such the proposed feedback modalities. While joint space feedback alone can be quite challenging for the user, it does not suffer from the redundancy problem. Considering the human body has many redundant degrees of freedom and based on the preference results, we, therefore, deem audio feedback in joint space as the preferred method for worker's pose reconfiguration application. Nevertheless, a combination of joint space feedback and endpoint space feedback might be used in some cases.

6 Conclusion

In this study, we have designed a multi-modal feedback system for pose correction intended for improving human ergonomics during task execution. The proposed feedback system was made up of non-physical types of feedback modalities. Visual feedback was used to carry out a large range of body movements, while speech-based audio feedback was used for minor pose adjustments once the user was close enough to the desired pose. Through this feedback system, we were successfully able to combine the advantages of visual feedback and audio feedback.

We hypothesised that the proposed multi-modal feedback system would provide a better performance as compared to the existing non-physical uni-modal feedback systems. While multi-modal feedback generally achieved similar performance as visual feedback in objective measures, it did outperform it in subjective assessment.

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