Vocal Pain Expression Augmentation to Improve Interaction Accuracy in Virtual Robopatient

Namnueng Protpagorn[1], Leone Costi[1], Thilina Dulantha Lalitharatne[1,2], Ilana Nisky[1,3] and Fumiya Iida[1]

***Abstract*— Palpation is a method use by physicians to physically examine patients using fingers or hands to diagnose any disease or illness. Vocal pain expressions of the patient during palpation are considered as important feedback to assess the conditions. Although recent technological advances has enabled development of medical simulators for physician to train the palpation procedures, incorporating vocal pain expressions to these simulators has been understudied. In this paper, we present a vocal pain expression augmentation for a robopatient to be used in abdominal palpation training. Our virtual robopatient builds upon a virtual abdomen and a face which can render facial pain expressions together with vocal pain expressions. In a user study (N=26), we test the vocal pain augmented virtual robopatient against a system without vocal pain expressions in a palpation task to estimate the maximum pain point within the virtual abdomen. We demonstrate that the vocal pain augmented virtual robopatient leads to statistically significant improvements in localizing the maximum pain without compromising the position estimation time.**

I. Introduction

Medical errors cost up to 98,000 lives in the United States of America [1] and more than £98 million to the NHS England every year [2]. The number of accidents can be reduced through improvement in training of medical professionals by diversifying training methods and increasing the training frequency [3], [4]. Among the skills that need to be trained by medical professionals, physical examination is a crucial one that could take years to train [5]. Physical examination is composed of four phases: inspection, palpation, auscultation, and percussion [6]. Among them, palpation has been widely studied in simulation [7] and in real life [8], [9] due to the intrinsically dexterous and sensitive nature of the task.

Palpation is part of physical examination using fingers or hands to diagnose disease or illness. Palpation is an examination method based on multisensory feedback: facial expression, haptic and auditory feedback. Traditional methods used to train palpation skills include live demonstrations followed by students practising these skills under supervision. In the students' own time, they can continue to train these skills using physical mannequins or tissue phantoms [10]. Students can also practice their physical examination skills on standardised patients (SPs) who are professionally trained actors acting as patients. Training on SPs is effective [11] but this method is time-consuming because of SP training and SPs skills maintenance.

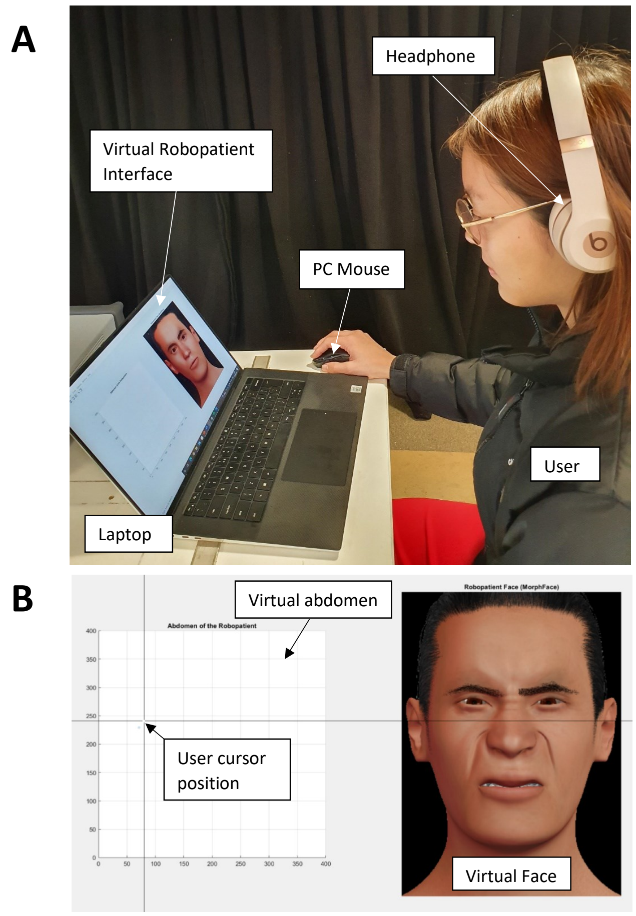

Fig. 1: Implemented virtual Robopatient interface **A** shows a participant performing a trial in front of the laptop while wearing a headphone. **B** shows the developed virtual robotic patient interface. The participants explore the virtual abdomen to find the face with highest pain expression while listening to the pain vocal expressions.

Medical training simulators can provide a safe and controlled environment for medical students to practice their physical examination skills. Feedbacks for palpation training setups range from haptic to visual. Haptic feedback setups range from modelling tumours using granular jamming [12] to physical systems using interchangeable organs [13]. Visual feedback includes visualising colours and texture of tumours

This work was supported by the SMART project, European Union's Horizon 2020 research and innovation under the Marie Sklodowska-Curie (grant agreement ID 860108), and EPSRC RoboPatient project EP/T00519X/1 (University of Cambridge) and EP/T00603X/1 (Imperial College London).

[1]Bio Inspired Robotics Laboratory, Department of Engineering, University of Cambridge, UK
[2]Dyson School of Design Engineering, Imperial College London, UK
[3]Biomedical Robotics Lab, Ben-Gurion University of the Negev, Israel

Manuscript 80 submitted to 2022 9th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). Received February 28, 2022.

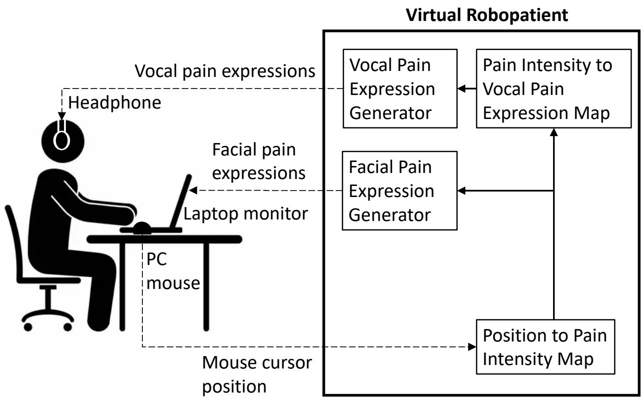

Fig. 2: Overview of the virtual Robopatient interface. It consists of a position to pain intensity map, a pain intensity to vocal pain expression map, a facial pain expression generator and a vocal pain expression generator. The interface takes the user mouse cursor position as the input and generates pain facial and vocal expressions as outputs.

[14] or rendering facial expressions [15]. On the other hand, audio feedback has been identified by doctors as important feedback during palpation [16]. Despite this, there is only a limited number of medical simulators with audio feedback capabilities. SimMan 3G [17] and Pediatric HAL [18] are examples of successful commercialised medical simulators with audio feedback. SimMan 3G [17] is a patient simulator from Laerdal Medical for training rapid assessment of trauma emergencies. On the other hand, the Pediatric HAL [18] is a pediatric patient simulator that can render dynamic facial expressions, movement, and speech.

Some evidence shows hearing someone's voice allows you to more accurately detect the emotion compared to looking at the facial expressions [19]. Many researchers have confirmed that humans react faster to sound compared to light and touch. The mean auditory reaction time is 140–160 ms, the mean visual reaction time is 180–200 ms and the mean tactile reaction time is 155 ms [20]. This could be because it takes $8-10$ ms for auditory stimulus to reach the brain while approximately 20–40 ms for visual stimulus. Research has also shown that the reaction time to combined stimulus events is $20-40$ ms shorter than to visual events alone [21]. These findings together with the scarcity of medical simulators with audio feedback suggest the importance of adding pain sounds to the existing palpation simulators.

This paper present a vocal pain expression augmentation for a robopatient to be used in abdominal palpation training. The implemented virtual robotpatient interface is presented in Fig. 1 and an overview on how the virtual robotpatient interface is built is shown in Fig. 2. The virtual robopatient consists of a position to pain intensity map, a pain intensity to vocal pain expression map, a facial pain expression generator and a vocal pain expression generator. In a user study ($N = 26$), we tested the vocal pain augmented virtual robopatient against a robopatient without vocal pain expressions in a palpation task where the participants are asked to estimate the maximum pain point located with a virtual abdomen. We demonstrate that the vocal pain augmented virtual robopatient leads to statistically significant improvements in localizing the maximum pain without compromising the position estimation time.

The rest of the paper is organized as follows: Section II discusses the experimental setup together with a detailed explanation on each subsystem of the virtual robopatient. Experiments and results are presented in Section III. Finally in Section IV, important conclusions are made, while suggesting possible future directions.

II. Methods

A. Experimental Setup

The overview of the virtual robopatient interface is summarised in in Fig. 2. It mainly consists of a position to pain intensity map, a pain intensity to vocal pain expression map, a facial pain expression generator and a vocal pain expression generator. The interface takes the user mouse cursor position as the input and generates pain facial and vocal expressions as outputs. Total virtual robopatient interface is implemented on MATLAB R2021b. The system consists of a $400\ px \times 400\ px$ virtual abdomen in the left pane of Fig. 1B and the simulated series of facial pain expressions in the right pane of Fig. 1B, generated using Makehuman software, that reacts to the user mouse position in the right pane. A PC mouse, a Beats Solo3 On-Ear Headphone and a full 15 $inch$ screen of a laptop are provided with the participants to conduct the experiment in a quiet and distraction-free environment. The entire virtual robopatient interface was implemented in a laptop with Intel Core i7-10750H with 16GB RAM operating on Windows 10 Pro.

B. Pilot Study: Choosing 5 pain sounds

Selecting proper human pain sounds is important for realising the virtual robopatient with vocal pain expression augmentation. Therefore, as the first step, we choose 5 pain sounds using a pilot study. A group of 6 participants which consists of 3 STEM background and 3 humanities background was given 35 pain sounds from a database once and rated the painfulness of the audio pain expression on a 0 to 10 scale, where 10 is the maximum pain. The experiment was done in a quiet and distraction-free environment. All the participants were given the same headphones that plays the same volume of the pain sounds in the same order. Each response is normalised and the mean of the ratings is calculated to show the average painfulness of each pain sound. The variances of the ratings are calculated and five sounds with the lowest variances are selected to signify the majority agreement. Only pain sounds with ratings 2,3,4,5,6 were chosen because the pain sounds with ratings of 6 or above were too unrealistic for palpation application since the pain level of the patient during palpation should be just above the discomfort level [22], [23].

Manuscript 80 submitted to 2022 9th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). Received February 28, 2022.

C. Position to pain intensity map

The (x_t, y_t) coordinate of the tumour or the maximum pain point is randomised in the 300 px $\times$ 300 px virtual force sensor platform using the `300*rand(1)` function on MATLAB.

The pain map is determined from the location of the tumour using a 2D Gaussian equation:

$$\text{Pain} = \frac{k}{\sigma\sqrt{2\pi}} e^{-\frac{(x-x_t)^2+(y-y_t)^2}{2\sigma^2}} \tag{1}$$

Where constant k is calibrated so that the pain values lie between 0 and 100, (x, y) is the coordinate of the user click on the abdominal phantom and the standard deviation σ is 0.0005. The distribution of pain around the maximum pain point is assumed to be Gaussian due to the fact that most biological data is normally distributed. Examples of such biological data include the height [24] and mean arterial blood pressure in healthy adults. Similarly, acute pain such as bruises and cuts is concentrated at the site of the damage and decreases as the distance from the damage site increases. This mimics the behaviour of a Gaussian distribution.

D. Pain intensity to vocal pain expression map and vocal pain expression generator

The virtual robopatient will make the pain sounds corresponding to the pain level in the pain intensity map and the pain intensity to vocal pain expression map. The pain level in the pain intensity map is divided into six segments: 0 - 50 (no sound), 50 - 65 (pain sound 1), 65 - 80 (pain sound 2), 80 - 90 (pain sound 3), 90-95 (pain sound 4), 95 - 100 (pain sound 5). If the pain level is lower than the pain threshold of 50, no pain sound is played and the state remains at the starting state. If the pain value is greater than the threshold of each level, then a pain sound of that level is played. After the sound is played, the audio system returns to its starting state, but the facial expression remains at the current state until the next click. If the participants click closer to the maximum pain point, the virtual robopatient will play more painful sounds according to higher pain levels. This pain to sound mapping method is demonstrated in Algorithm 1. As an example, if the user was to click on the virtual abdomen which resulted in the pain intensity of 66, the face of the virtual robopatient would change to match the intensity of the pain. The face remains the same until the next point is clicked but pain sound 2 is played once. In the next attempt, if the participant clicks closer to the maximum pain point with the pain intensity of 85, the facial expression becomes more painful and remains constant within attempts but pain sound 4 is played once.

This algorithm maps continuous 2D-Gaussian pain values to 5 discrete pain sounds. This is because when humans are experiencing acute pain, they make sudden and sharp noises for themselves and others to react instinctively from the surprise [25]. Since the sounds they make are discrete, it allows us to map the continuous pain values to discrete levels of sound.

Algorithm 1 Pain to sound mapping

```
Require: 0 ≤ pain ≤ 100
sound ← off
if 50 < pain ≤ 65 then
    sound ← painsound1
else
    if 65 < pain ≤ 80 then
        sound ← painsound2
    else
        if 80 < pain ≤ 90 then
            sound ← painsound3
        else
            if 90 < pain ≤ 95 then
                sound ← painsound4
            else
                if 95 < pain ≤ 100 then
                    sound ← painsound5
                end if
            end if
        end if
    end if
end if=0
```

E. Facial pain expression generator

The pain level in the pain intensity map lie between 0 and 100 according to the pain mapping function in Equation 1. Therefore, 100 images of a white male face with facial pain expressions based on 4 facial action units (AUs): AU4 (Brow Lowerer, AU7 (Lid Tight- ener), AU9 (Nose Wrinkler) and AU10 (Upper Lip Raiser) are rendered (using Makehuman software) and are directly matched with the pain intensity according to [26].

III. Experiment and Results

26 participants were recruited for the experiment. Participants were undergraduate and postgraduate students from the University of Cambridge. The average age of the participants is 23.5 with standard deviation of 3.5. The minimum age is 21 and the maximum age is 34. Participants had no visual impairment or hearing difficulties and no experience in medical simulation. 18 out of 26 participants were engineering students. 16 out of 26 were self-identified as male and 4 as female. All participants signed a consent form that indicates the purpose of the experiment, what the experiment involves and how the data is handled.

The experiment starts with a detailed instruction of the tasks. Participants will click on the left pane to palpate the abdomen, starting from a random point, and simultaneously analyse the facial expression or both facial expression and audio pain expression to determine the pain level. Participants' clicking motion imitates the pressing gesture during palpation and the maximum pain point mimics a sign of tumours in the abdomen. After the explanation, the instructor did one attempt of the experiment until the maximum pain point is found as an example for the participant. The participant will start the experiment when the example is over.

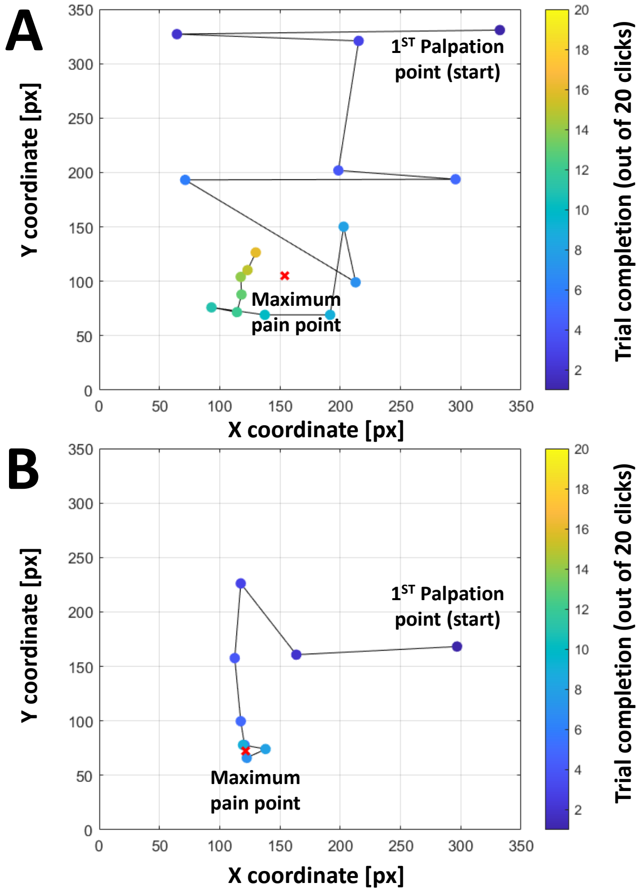

Fig. 3: Example performed trajectory by one of the participant under **A** sound condition and **B** no sound condition.

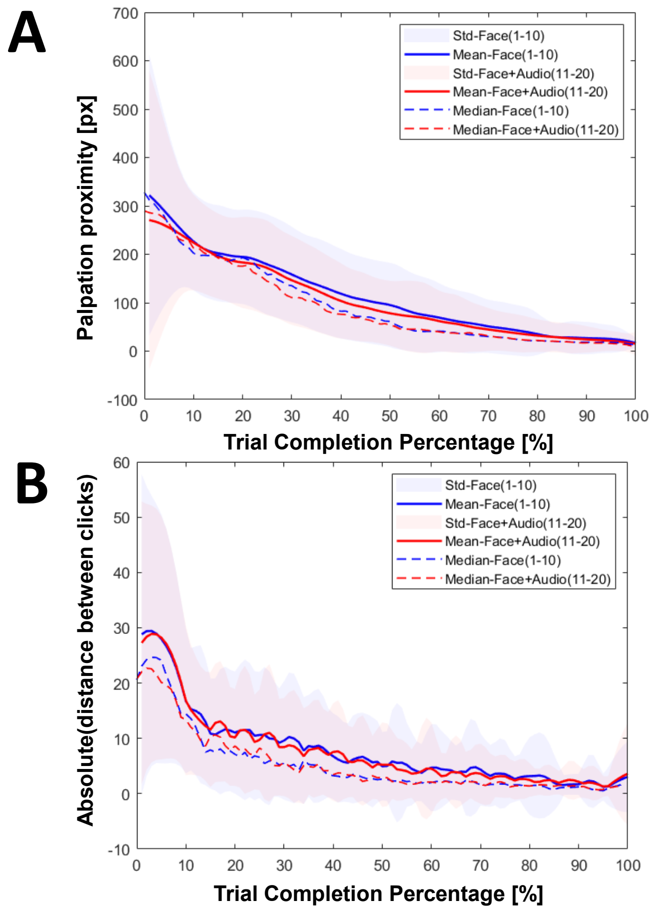

Fig. 4: **A** Palpation proximity, or the distance between click and the maximum pain point against the trial completion percentage for all participants. The trial completion percentage is measured by the ratio of number of clicks at the current attempt against the total number of clicks per trial. **B** The mean absolute distance between clicks against the percentage trial completion is measured by number of users click for all participants.

The experiment consists of 20 palpation trials per participant. The first group of participants performed 20 palpation trials without sound. The first group of the participants was the control group which consists of 10 participants. The reason for having a control group was to isolate the effect of sound independently from the natural learning of the task over time. The second group of participants performed the first 10 trials without sound and the next 10 trials with sound. There were 16 participants in the second group. In each trial, participants had a maximum of 20 clicks to find the maximum pain point since previous experiments suggest that participants could find the maximum points in less than 20 attempts. The experiment was done in one sitting. The average distance between the participants and the laptop screen was approximately 45 cm.

Fig. 3 shows an example of a trajectory map for one trial without sound and one trial with sound for one participant which includes the click location, palpation trajectory and the location of the tumour. Comparing Fig. 3A and 3B, it is clear that the trial with sound achieved higher accuracy and require less number of clicks to find the maximum pain point. Initially, there was no visual or audio feedback because the participant was far from the maximum pain point. The participant searched without any information and took a random approach in order to gain more information about the location of the maximum pain point. During the random search period, the distances between clicks are relatively high because the only information the participant had is that the maximum pain point is not close to their recent click. When the participant received some information from the feedback in the 10^{th} click, the participant knows that the maximum pain point is nearby and so the search strategy changes. The mean distance between clicks becomes smaller and the search pattern is less geometric as the trial completion percentage reaches 100%. Although Fig. 3 shows a trajectory of one participant, this observation is supported by the graphs Fig. 4B. Fig. 4A shows that as the trial completion percentage increases to 100%, the palpation proximity decreases as expected. Comparing Fig. 4A and Fig. 4B, there is a correlation between the decrease in palpation proximity and the decrease in the distance between clicks against time, suggesting that the change in strategy leading

Manuscript 80 submitted to 2022 9th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob). Received February 28, 2022.

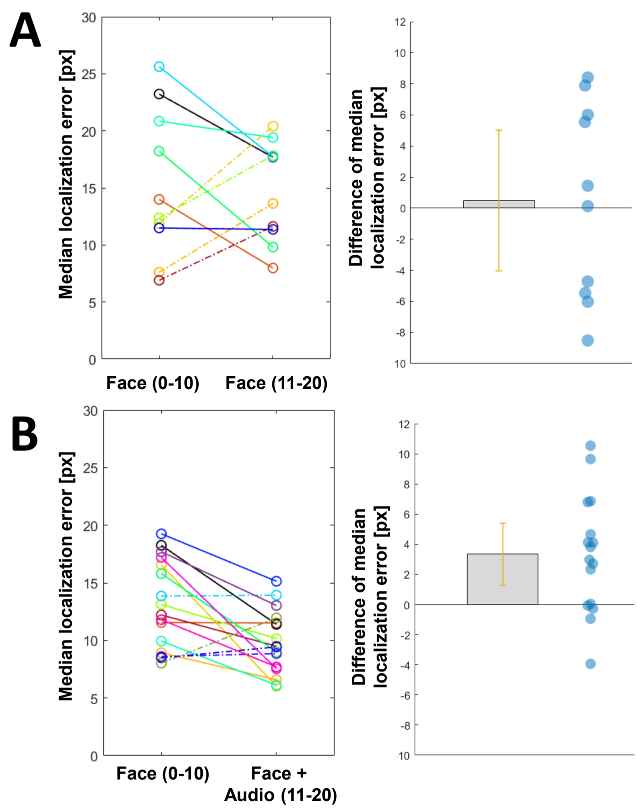

Fig. 5: The paired plot for the distribution of median localization error together with individual participant's performance scatter plot. **A** The participants carried out the experiment with only visual feedback for all 20 trials **B** The participants carried out the experiment first with only visual feedback for the first 1-10 trials and then with visual and audio feedback for the second 11-20 trials

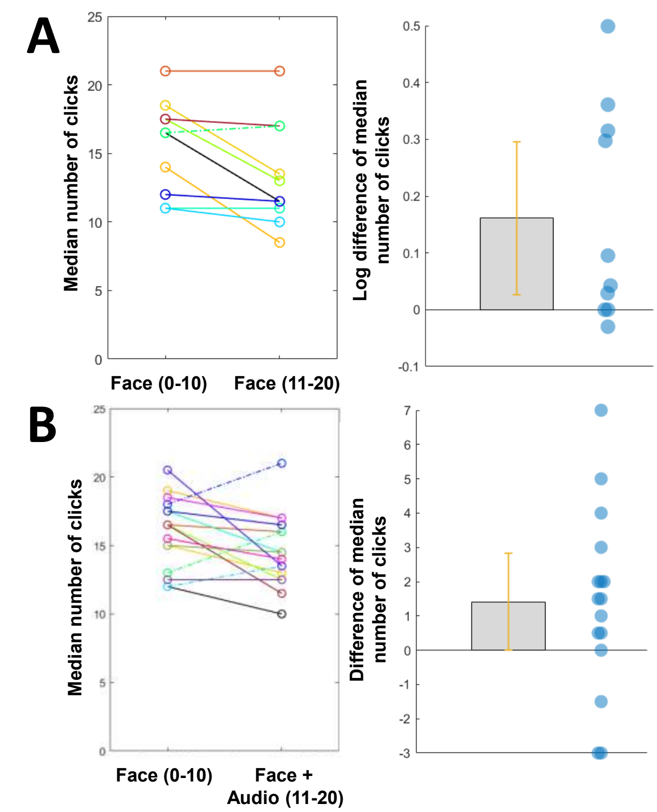

Fig. 6: The paired plot for the distribution of median number of clicks together with all the data presented as a scatter plot. **A** The participants carried out the experiment with only visual feedback for all 20 trials **B** The participants carried out the experiment first with only visual feedback for the first 1-10 trials and then with visual and audio feedback for the second 11-20 trials

to shorter movements could be due to the higher presence of pain-related information.

Fig. 5A left shows the paired plot for the distribution of median localization error of only visual feedback method for all participants. This is the control group and 6 out of 10 participants made larger errors in finding the maximum pain point in the second 10 trials compared to the first 10 trials. There is no statistical significance for the difference in the accuracy between the first 10 trials and the second 10 trials from Fig. 5A right ($t(9) = 0.235, p = 0.819$). The result of the control group proves that the effect of learning is not strong enough to produce a significant change in performance.

Fig. 5B left shows the paired plot for the distribution of median localization error of two feedback methods for all participants. 11 out of 16 participants found the maximum pain points with smaller median localization error ($Hedges'g = [0.12, 1.47]$), or larger accuracy of identifying the maximum pain point, when the system is integrated with sound.

Using the Anderson-Darling test, the results from this experiment is from a population with a normal distribution. A one sample t-test applied to differences of accuracy between the two methods showed statistically significant higher accuracy ($t(15) = -3.43, p = 0.004$) when adding audio pain expression to the facial feedback (Fig. 5A right).

The results show that there is a synergistic effect when sound is added to the virtual robopatient. It is clear that this effect comes from the addition sound, rather than participants improving through learning, because the control experiment in Fig. 5A does not demonstrate comparable results. The impact of learning on the experiment is not significant.

Fig. 6A left shows the paired plot for the distribution of number of clicks of only visual feedback method for all participants. 9 out of 10 found the maximum pain point in less number of clicks. This is because participants familiarise themselves with the facial expression feedback in the second 10 trials and were able to find maximum pain point in a smaller number of clicks with statistical significance($t(9) = 2.70, p = 0.025$) and with a similar localization accuracy as the first 10 trials.

Fig. 6B left shows the paired plot for the distribution of number of clicks of two feedback methods for all participants. 13 out of 16 Participants found the maximum pain point in less number of clicks when the system is integrated with sound in Fig. 6. The number of clicks indicates the time and the confidence of the participants in finding the maximum pain point. Though this may suggest that participants are able to find the maximum pain point in less time, this result is not statistically significant ($t(15) = 2.12, p = 0.051$). We believe that the statistically significant reduction in number of clicks in Fig. 6A is due to participants familiarising with the base setup. On the other hand, participants performing the second 10 trials with additional audio feedback need to adapt to a new system. Thus, there is no significance between the first 10 trials and the last 10 trials. Therefore, the result of this experiment demonstrates that when the system is integrated with sound the accuracy of locating the maximum pain point will increase without compromising on the time taken.

Informal post experiment discussions with the participants revealed that "adding sound definitely helps with locating maximum pain", supporting both results in Fig. 5 and 6. A possible reason for such an increase in performance could be due to the fact that, every second, human body sends 11,000,000 bits of information to the brain but the conscious mind can only process 120 bits of information [27]. We believe that the reason why using multisensory signals enables faster response could be because human brain requires more processing time to compress 10,000,000 bits of visual information [28] compared to 100,000 bits of auditory information [29] per second. Around the maximum pain point, 1 bit additional of auditory information would provide more information compared to 1 additional bit of visual information and hence the accuracy of maximum pain localization increases when audio pain expressions are added to the virtual robopatient. Additionally, the continuous nature of the facial expression output makes visual feedback more difficult to distinguish near the maximum pain point. Given the participants had time to learn the simulation with only visual feedback, adding discrete audio feedback that correlates with the initial stimulus creates a synergistic effect. The hybrid audio-visual feedback allows participants to notice more features from the visual feedback which confirms and clarify the location of the maximum pain point. Hence, participants are able to find a more accurate maximum pain point overall.

IV. CONCLUSIONS

In this study, we presented a vocal pain expression augmentation for a Robopatient to be used in abdominal palpation training. 26 participants, of which 10 participants were the control group and 10 participants were the test group, conducted an experiment to find the maximum pain point using the virtual robopatient only with facial pain expressions and using the vocal pain expression augmented virtual robopatient. From the result of the experiment, of the 16 participants belonging to the test group 11 were able to find a more accurate maximum pain point when the virtual robopatient is integrated with vocal pain expressions. We demonstrated that the vocal pain augmented virtual robopatient leads to statistically significant improvements in localizing the maximum pain without compromising the position estimation time. There is a synergistic effect when vocal pain expressions is added to the virtual robopatient and therefore this could be considered a valid complementary feedback mode for abdominal palpation on virtual robopatients. Despite these advantages in the virtual robopatient interface, the current implementation has limitations. For example in the current approach, when a participant clicks a position to mimic the palpation, only a pre-determined force value is considered to be applied to the abdomen of the virtual robopatient. In reality however, physicians can apply enough force and/or vary his/her palpation force diagnosis a patient. Additionally, in this experiment the number of user clicks was used as a proxy for time because participants only received information after clicking and they were instructed to solve the task within a limited amount of clicks rather than time. To address this, we endorse future studies investigating the relationship between number of explored points and the overall experiment time. Future studies will also aim to incorporate sound into a physical robopatient [15] to realise and optimise the responses for medical training and remote palpation applications [30].

REFERENCES

[1] M. S. Donaldson, J. M. Corrigan, L. T. Kohn *et al.*, "To err is human: building a safer health system," 2000.

[2] R. A. Elliott, E. Camacho, D. Jankovic, M. J. Sculpher, and R. Faria, "Economic analysis of the prevalence and clinical and economic burden of medication error in england," *BMJ Quality and Safety*, vol. 30, pp. 96–105, 2 2021.

[3] D. A. Davis, M. A. Thomson, A. D. Oxman, and R. B. Haynes, "Changing physician performance: a systematic review of the effect of continuing medical education strategies," *Jama*, vol. 274, no. 9, pp. 700–705, 1995.

[4] R. Likic and S. R. Maxwell, "Prevention of medication errors: teaching and training," *British journal of clinical pharmacology*, vol. 67, no. 6, pp. 656–661, 2009.

[5] A. R. Danielson, S. Venugopal, J. M. Mefford, and S. O. Clarke, "How do novices learn physical examination skills? a systematic review of the literature," *Medical Education Online*, vol. 24, 1 2019. [Online]. Available: /pmc/articles/PMC6495115/ /pmc/articles/PMC6495115/?report=abstract https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6495115/

[6] N. L. of Medicine (US). Friends, *MedlinePlus*. National Institutes of Health and the Friends of the National Library of . . . , 2010.

[7] J. Palacio-Torralba, R. L. Reuben, and Y. Chen, "A novel palpation–based method for tumor nodule quantification in soft tissue—computational framework and experimental validation," *Medical and Biological Engineering and Computing*, vol. 58, no. 6, pp. 1369–1381, 2020.

[8] J. Konstantinova, M. Li, G. Mehra, P. Dasgupta, K. Althoefer, and T. Nanayakkara, "Behavioral characteristics of manual palpation to localize hard nodules in soft tissues," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 6, pp. 1651–1659, 2014.

[9] J. Konstantinova, G. Cotugno, P. Dasgupta, K. Althoefer, and T. Nanayakkara, "Palpation force modulation strategies to identify hard regions in soft tissue organs," *PLoS ONE*, vol. 12, no. 2, pp. 1–24, 2017.

[10] W. C. McGaghie, S. B. Issenberg, M. E. R. Cohen, J. H. Barsuk, and D. B. Wayne, "Does simulation-based medical education with deliberate practice yield better results than traditional clinical education? a meta-analytic comparative review of the evidence," *Academic medicine: journal of the Association of American Medical Colleges*, vol. 86, no. 6, p. 706, 2011.

[11] H. K. Walker, W. D. Hall, and J. W. Hurst, "Clinical methods: the history, physical, and laboratory examinations," 1990.

[12] S. B. Rørvik, M. Auflem, H. Dybvik, and M. Steinert, "Perception by palpation: Development and testing of a haptic ferrogranular jamming surface," *Frontiers in Robotics and AI*, p. 311, 2021.

[13] A. Rethy, J. O. Sæternes, J. Halgunset, R. Mårvik, E. F. Hofstad, J. A. Sánchez-Margallo, and T. Langø, "Anthropomorphic liver phantom with flow for multimodal image-guided liver therapy research and training," *International journal of computer assisted radiology and surgery*, vol. 13, no. 1, pp. 61–72, 2018.

[14] A. Shafikov, T. Tsoy, R. Lavrenov, E. Magid, H. Li, E. Maslak, and N. Schiefermeier-Mach, "Medical palpation autonomous robotic system modeling and simulation in ros/gazebo," *Proceedings - International Conference on Developments in eSystems Engineering, DeSE*, vol. 2020-December, pp. 200–205, 12 2020.

[15] T. D. Lalitharatne, Y. Tan, L. He, F. Leong, N. V. Zalk, S. D. Lusignan, F. Iida, and T. Nanayakkara, "Morphface: A hybrid morphable face for a robopatient," *IEEE Robotics and Automation Letters*, vol. 6, pp. 643–650, 4 2021.

[16] "The effect of real time auditory feedback during palpation of a simulated lumbar spine in the education of physical therapy students." [Online]. Available: https://www.scitechnol.com/abstract/the-effect-of-real-time-auditory-feedback-during-palpation-of-a-simulated-lumbar-spine-in-the-education-of-physical-therapy-studen-9212.html

[17] "Simman 3g advanced patient simulator — products and prices." [Online]. Available: https://laerdal.com/gb/doc/85/SimMan-3G

[18] "Pediatric hal s2225 - advanced pediatric patient simulator - gaumard." [Online]. Available: https://www.gaumard.com/s2225/

[19] M. W. Kraus, "Voice-only communication enhances empathic accuracy." *American Psychologist*, vol. 72, no. 7, p. 644, 2017.

[20] R. J. Kosinski, "A literature review on reaction time," *Clemson University*, vol. 10, no. 1, 2008.

[21] S. C. Gielen, R. A. Schmidt, and P. J. Van Den Heuvel, "On the nature of intersensory facilitation of reaction time," *Perception & psychophysics*, vol. 34, no. 2, pp. 161–168, 1983.

[22] A. Reuben, "Examination of the abdomen," *Clinical Liver Disease*, vol. 7, pp. 143–150, 6 2016.

[23] C. R. Macaluso and R. M. McNamara, "Evaluation and management of acute abdominal pain in the emergency department," *International Journal of General Medicine*, vol. 5, pp. 789–797, 2012.

[24] M. F. Schilling, A. E. Watkins, and W. Watkins, "Is human height bimodal?" *The American Statistician*, vol. 56, no. 3, pp. 223–229, 2002.

[25] J. R. Parker and J. Heerema, "Audio interaction in computer mediated games," *International Journal of Computer Games Technology*, vol. 2008, 2008.

[26] Y. Tan, "Realistic pain expression simulation using perception-based weighted action units," Apr 2021. [Online]. Available: osf.io/6nhw3

[27] "Why it's so hard to pay attention, explained by science." [Online]. Available: https://www.fastcompany.com/3051417/why-its-so-hard-to-pay-attention-explained-by-science

[28] K. Kreeger, "Penn researchers calculate how much the eye tells the brain," *Penn Medicine News*, 2006.

[29] "information theory - physiology — britannica." [Online]. Available: https://www.britannica.com/science/information-theory/Physiology

[30] L. Costi, L. Scimeca, P. Maiolino, T. D. Lalitharatne, T. Nanayakkara, R. Hashem, and F. Iida, "Comparative analysis of model-based predictive shared control for delayed operation in object reaching and recognition tasks with tactile sensing," *Frontiers in Robotics and AI*, vol. 8, p. 313, 9 2021.