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Bidirektionale Interaktion von Mensch und Roboter beim Bewegungslernen - Visuelle Wahrnehmung von Roboterbewegungen

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Bidirektionale Interaktion von Mensch und Roboter beim Bewegungslernen

Visuelle Wahrnehmung von Roboterbewegungen
Zur Erlangung des Grades eines Doktors der Naturwissenschaften (Dr. rer. nat.)
genehmigte Dissertation von Gerrit Kollegger aus Frankfurt am Main
Tag der Einreichung: 19. Mai 2020, Tag der Prüfung: 16. Juli 2020

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TECHNISCHE UNIVERSITÄT DARMSTADT

Fachbereich Humanwissenschaften
Institut für Sportwissenschaft

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Zusammenfassung

In den vergangenen Jahrzehnten haben sich die Arbeitsbereiche von Menschen und Robotern zunehmend gegenseitig durchdrungen. Interaktionen zwischen Mensch und Roboter sind in vielen Lebensbereichen, z. B. Industrie, Medizin, Rehabilitation und Sport gegenwärtig.
Während Roboter bisher vorwiegend starr programmiert wurden, hat sich in den letzten Jahren ein Paradigmenwechsel hin zu einer anpassungsfähigen, lernenden Programmierung vollzogen. Basierend auf diesem neuen Ansatz der Programmierung tritt eine direkte, teils physische Interaktion zwischen Mensch und Roboter zunehmend in den Fokus der Entwicklung und eröffnet ein bisher ungeahntes Potential zur Weiterentwicklung der Mensch-Roboter-Interaktion.
Die Beziehung von Mensch und Roboter ist von vielen, teils extremen Unterschieden zwischen den beiden Systemen gekennzeichnet (Verfügbare Sensorik, Anzahl der Freiheitsgrade, Anzahl der Muskeln/Aktuatoren sowie Integrationsgrad von Sensorik und Aktuatorik). Diese Unterschiede erweisen sich für die beiden Systeme in einem isolierten Bewegungslernprozess teils als Vor- und teils als Nachteil.

Der Frage, wie sich die Vorteile der beiden Systeme in einem gemeinsamen bidirektionalen Bewegungslernprozess optimal kombinieren lassen, geht das Projekt *Bidirectional Interaction between Human and Robot when learning movements* nach. Im Rahmen dieses interdisziplinären Forschungsprojektes sollen die Erkenntnisse aus den Bereichen der Sportwissenschaft und der Informatik kombiniert und die wissenschaftliche Basis für ein verbessertes Mensch-Roboter-Training gelegt werden.
Das Projekt unterteilt sich dabei in vier Teilbereiche: die bidirektionale Interaktion zweier Menschen, die unidirektionale Interaktion von Mensch und Roboter (zwei Richtungen) sowie die bidirektionale Interaktion von Mensch und Roboter.

In dieser Dissertation werden drei Artikel zu der beschriebenen Thematik vorgestellt. Der erste Artikel beschreibt Ziele und Struktur des Forschungsprojekts sowie drei exemplarische Studien zu den ersten drei Teilbereichen des Projekts. Aufbauend auf den Erkenntnissen einer der vorgestellten Studien zur Bedeutung der Beobachtungsperspektive beim Bewegungslernen, fokussieren die beiden darauf folgenden Artikel die *visuelle Wahrnehmung von Roboterbewegungen durch den Menschen*.

Der Beschreibung des Projekts in Zielen und Struktur schließt sich im Artikel I die Vorstellung von drei exemplarischen Untersuchungen an. Die erste Studie betrachtet die bidirektionale Interaktion in Mensch-Mensch-Dyaden. Sie verifiziert einen prototypischen, dyadischen Bewegungslernprozess und identifiziert relevante Themen, die auf Mensch-Roboter-Dyaden übertragen werden können.
Zur unidirektionalen Interaktion zwischen Mensch und Roboter werden zwei Studien vorgestellt. Im Bereich des Lernens eines Roboters von einem Menschen wird eine iterative Feedbackstrategie eines Roboters beschrieben. Eine Untersuchung zur Bedeutung der Beobachtungsperspektive beim Bewegungslernen von Mensch und Roboter bearbeitet den Bereich des unidirektionalen Lernens eines Mensches von einem Roboter. Basierend auf dieser Untersuchung ergeben sich die Fragestellungen, die in den folgenden beiden Artikeln untersucht werden.

Während viele Studien die Wahrnehmung von biologischen Bewegungen untersucht haben, befassen sich nur wenige Ansätze mit der Wahrnehmung von nichtbiologischen Roboterbewegungen. Um diese Lücke zu schließen, werden im Artikel II zwei aufeinander aufbauende Studien zur Wahrnehmung von Roboterputtbewegungen durch den Menschen vorgestellt. Es konnte gezeigt werden, dass eine Leistungsvorhersage der gezeigten Roboterputtbewegungen nur bei Sichtbarkeit der vollständigen Bewegung möglich sind. Insbesondere die Ausschwungphase scheint eine Vielzahl an räumlich-zeitlichen Informationen bereit zu stellen, die einen großen Einfluss auf die Leistungsvorhersage besitzen.

Aufbauend auf den bisher gewonnenen Erkenntnissen wird im Artikel III eine Studie vorgestellt, die versucht, die für die Ableitung von räumlich-zeitlichen Informationen wichtigen Bewegungselemente zu identifizieren. Im Rahmen der vorgestellten Untersuchung wurden die gezeigten Roboterputtbewegungen teilweise manipuliert. Wichtige Bewegungselemente, z. B. Roboter, Schläger oder Ball, wurden ausgeblendet.

Zusammenfassend betrachtet diese Dissertation die visuelle Wahrnehmung von Roboterbewegungen durch den Menschen am Beispiel der Puttbewegung im Golf. Der Hauptbeitrag dieser Arbeit sind Erkenntnisse, die in einen bidirektionalen Bewegungslernprozess von Mensch-Roboter-Dyaden überführt werden können. Aus der Arbeit ergeben sich weiterführende Forschungsansätze und Fragestellungen, die eine hohe Relevanz für die Weiterentwicklung der Interaktion von Mensch und Roboter besitzen.

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Abkürzungsverzeichnis

AE absolute error

BIMROB Bidirectional Interaction between Human and Robot when learning movements

BKAT Bildkartenauswahltest

CE constant error

D distance

DoF degrees of freedom

DR delayed retention

ER early retention

FiF Forum for Interdisciplinary Research

FLE flash-lag effect

F-RCHB Full vision with visible Robot, Club, Clubhead and Ball

F-RCH Full vision with visible Robot, Club, Clubhead and invisible Ball after impact

F-B Full vision with visible Ball and inivisible Club, Clubhead Ball after impact

F-CHB Full vision with visible Robot, Club, Clubhead and Ball - ändern

F-HB Full vision with visible Robot, Club, Clubhead and Ball - ändern

F-CH Full vision with visible Robot, Club, Clubhead and Ball - ändern

F-H Full vision with visible Robot, Club, Clubhead and Ball - ändern

F-H Abkürzungen der cues ergänzen

I-RCHB Incomplete vision with visible Robot, Club, Clubhead and Ball

KSD Kinematics Specify Dynamics

MRT mental rotation test

PST Picture Selection Test

rd radial distance

RMSE root-mean-square error

VC vision condition

VE variable error

1 Einleitung

Die Lebens- und Arbeitsbereiche von Menschen und Robotern haben sich in den vergangenen Jahrzehnten zunehmend durchdrungen. Insbesondere in den komplexen Produktionsprozessen der Industrie, z. B. Autoindustrie, sind Roboter neben dem Menschen ein unverzichtbarer Bestandteil geworden.

Industrieroboter sind heutzutage in der Lage, Menschen zu entlasten und monotone Tätigkeiten mit hoher Präzision und Geschwindigkeit auszuführen. Im Bereich der Medizin haben Roboter in der direkten Interaktion mit Menschen in den letzten Jahren rasant an Bedeutung gewonnen. Spezialisierte Systeme werden bei Operationen, Rehabilitation und Pflege eingesetzt (z. B. Stein, Hughes, Fasoli, Krebs und Hogan, 2005). Im Sport finden sich zunehmend Robotersysteme, insbesondere in Form von Mess- und Trainingsplätzen, z. B. Rudersimulator (Rauter, von Zitzewitz, Duschau-Wicke, Vallery und Riener, 2010) und Golftrainer (Camarano et al., 2015). Sportliche Bewegungen finden sich vermehrt in den wissenschaftlichen Forschungsarbeiten zur Robotik, insbesondere im Bereich der autonomen Systeme, z. B. Tischtennis (Koç, Maeda und Peters, 2018; Muelling, Boularias, Mohler, Schölkopf und Peters, 2014; Wang, Boularias, Mülling, Schölkopf und Peters, 2017).

In den letzten Jahren hat sich ein Paradigmenwechsel vollzogen. Wurden Roboter bisher starr programmiert, implementiert sich zunehmend eine anpassungsfähige selbstlernende Programmierung. Während Arbeitsräume klassischer Industrieroboter von denen des Menschen strikt getrennt waren, treten direkte Interaktionen zwischen Mensch und Roboter zunehmend in den Vordergrund. Daraus resultiert ein neuartiger Ansatz des gemeinsamen Lernens von Mensch und Roboter, der bisher ungeahntes Potential zur Weiterentwicklung der Mensch-Roboter-Interaktion besitzt und die Einsatzbereiche von Robotern nachhaltig verändern kann.

Bisher ist die Interaktion von Mensch und Roboter beim gemeinsamen Bewegungslernen wenig erforscht und ihre Dynamik wenig verstanden. Geprägt ist dieses Wissensdefizit insbesondere durch die unterschiedlichen Grundlagen der Hard- und Software von Mensch und Roboter. Dies sind:

1) Die Nutzung der verfügbaren Sensorik. Während der Mensch zahlreiche redundante Sensoren nutzt, verfügen Roboter meistens nur über eine sehr eingeschränkte Sensorik.

2) Der Mensch verfügt über eine große Anzahl an Gelenken mit etwa 250 Freiheitsgraden (DoFs), während heutige Roboter zwischen drei (einfache Robotersysteme) und 39 DoFs (humanoide Roboter) besitzen.

3) Dievinsgesamt 656 einzelnen Muskeln des Menschen ermöglichen eine sehr differenzierte, teils redundante Ansteuerung der einzelnen Gelenke und Freiheitsgrade. Die Konstruktion von Robotern zielt darauf ab, alle Freiheitsgrade mit möglichst einem einzigen Motor anzusteuern.

4) Die redundante Sensorik und Aktuatorik des Menschen bilden ein vollständig integriertes System, das über ein komplexes Zusammenspiel zahlreicher Bereiche des menschlichen Gehirns abgebildet wird. Die Verarbeitung von Sensorinformationen sowie die Steuerung der Bewegung erfolgt in

parallelisierten Prozessen. Robotersysteme verfügen über einen geringeren Grad an Parallelisierung der Rechenprozesse, weisen dagegen aber eine höhere Rechengeschwindigkeit auf.

Es wird deutlich, dass sich das biologische System des Menschen sehr stark von den technischen Systemen des Roboters unterscheidet.

Die benannten Unterschiede der beiden Systeme können sich in einem Bewegungslernprozess als Vor- oder Nachteil für das jeweilige System erweisen. Nach Bernstein (1967) ist zu Beginn eines Bewegungslernprozesses die große Zahl an Freiheitsgraden für die Entwicklung stabiler Bewegungsprozesse nachteilig (Bernstein-Problem). Zunächst schränkt der Mensch seine Freiheitsgrade ein, um sie im weiteren Verlauf des Bewegungslernprozesses, jedoch Stück für Stück wieder freizugegeben. Dagegen profitieren Robotersysteme zu Beginn des Lernprozesses von einer geringen Anzahl an Freiheitsgraden sowie von einem sehr kontrollierten Krafteinsatz, besitzen aber nur wenige Möglichkeiten, die Bewegung zu variieren. Diese unterschiedlichen Eigenschaften haben bereits Einfluss auf die Programmierung von neuen Robotersystemen genommen. So verfügen sie über Algorithmen zum Demonstrationslernen: Ein Mensch führt die Bewegung des Roboters und dieser leitet daraus die zu erlernende Bewegung ab. Der entgegengesetzte Weg wird z. B. in der Rehabilitation genutzt, indem Roboter den Menschen bei bestimmten Bewegungen, z. B. beim Gehen, führen. Diese Prozesse laufen jeweils unidirektional ab, der Mensch lehrt den Roboter bzw. der Roboter lehrt den Menschen. Bisher wenig beachtet ist die bidirektionale Interaktion der beiden Systeme.

1.1 BIMROB-Projekt

Das skizzierte Forschungsdefizit im Bereich der bidirektionalen Interaktion von Mensch und Roboter beim Bewegungslernen nimmt das Projekt *Bidirectional Interaction between Human and Robot when learning movements* (BIMROB) im Rahmen einer interdisziplinären Kooperation zwischen Sportwissenschaft und Informatik auf. Kernidee des BIMROB-Projektes ist, die Erkenntnisse aus beiden Forschungsdisziplinen zu kombinieren, um die wissenschaftlichen Grundlagen für ein verbessertes Robotertraining zu legen sowie die Entwicklung neuer Trainings- und Rehabilitationsgeräte zu ermöglichen. Auf Seiten der Informatik beziehen sich diese Erkenntnisse auf Ansätze, mit denen Roboter präzise und reproduzierbare Bewegungen erlernen und ausführen können. Die Sportwissenschaft steuert das Verständnis einer flexiblen Bewegungssteuerung unter Integration von Wahrnehmung bei.

Das Projekt kann in vier Hauptbereiche eingeteilt werden (siehe Abbildung 1.1):

1) Bidirektionale Interaktion von Mensch-Mensch-Dyaden - zwei Menschen lernen gemeinsam. In dieser Konstellation wird untersucht, welche Prozesse bei einem gemeinsamen Bewegungslernprozess zweier Menschen stattfinden. Basierend auf diesen Erkenntnissen sollen relevante Erkenntnisse in die Interaktion von Mensch-Roboter-Dyaden übertragen werden;

2) Unidirektionale Interaktion in Mensch-Roboter-Dyaden - Roboter lernen von Menschen. In diesem Bereich steht die Entwicklung von Algorithmen zum maschinellen Lernen im Vordergrund;

3) Unidirektionale Interaktion von Mensch-Roboter-Dyaden - Menschen lernen von Robotern. Dieser Teilbereich bearbeitet die Entwicklung möglicher Informationsschnittstellen zwischen Roboter und Mensch sowie an menschliche Lernstrategien angepasste Informationsaufbereitung durch Robotersysteme;

4) Bidirektionale Interaktion von Mensch-Roboter-Dyaden - Mensch und Roboter lernen gemeinsam. In diesem finalen Arbeitsbereich sollen die gewonnenen Erkenntnisse zusammengeführt werden, um einen gemeinsamen Bewegungslernprozess effizient und effektiv zu gestalten.

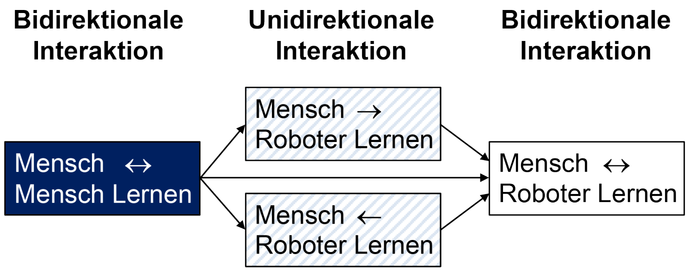

Abbildung 1.1: Struktur des BIMROB-Projektes (mod. nach Wiemeyer und Peters, 2017).

Die Vision des Projekts ist die Entwicklung eines bidirektionalen Bewegungslernprozesses. Ein mögliches Szenario beinhaltet zunächst eine gemeinsame Lernphase von Mensch und Roboter, gefolgt von einer individuellen Selbstoptimierung der Bewegung in getrennten Übungen. Abschließend werden Mensch und Roboter wieder zusammengebracht und kombinieren die optimierten Bewegungen (siehe Abbildung 1.2).

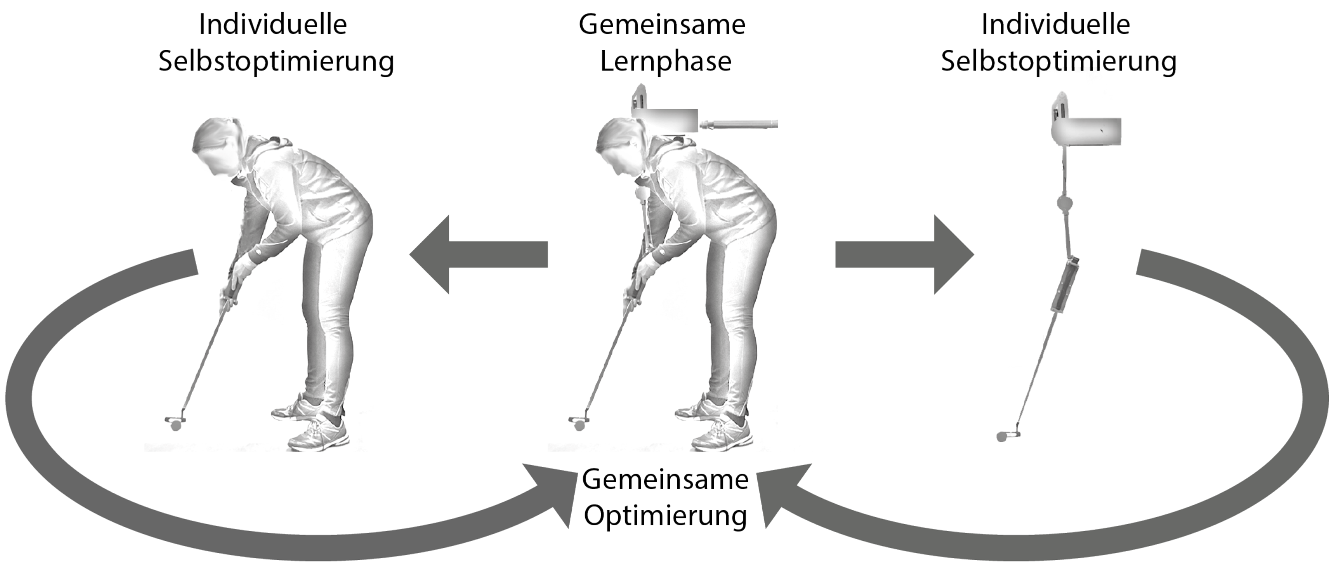

Abbildung 1.2: Potentielles bidirektionales Bewegungslernszenario.

Der visuellen Wahrnehmung von Roboterbewegungen kommt sowohl im Rahmen der unidirektionalen Interaktion (Mensch lernt vom Roboter) als auch während der bidirektionalen Interaktion (Mensch und Roboter lernen gemeinsam) eine große Bedeutung zu. In der bisherigen Forschung fand die Wahrnehmung von nicht biologischen Bewegungen, z. B. Roboterbewegungen, trotz ihrer großen Bedeutung für die Interaktion von biologischen und technischen Systemen nur wenig Aufmerksamkeit.

1.2 Überblick

Der beschriebene Forschungsansatz des BIMROB-Projekts wird in den folgenden drei Kapiteln - die jeweils einer Veröffentlichung entsprechen - dargestellt. Einer allgemeinen Beschreibung der Kernidee und der Struktur des BIMROB-Projekts schließen sich drei exemplarische Untersuchungen zu unterschiedlichen Strukturbereichen des Projekts an (Artikel I), siehe Abbildung 1.3.

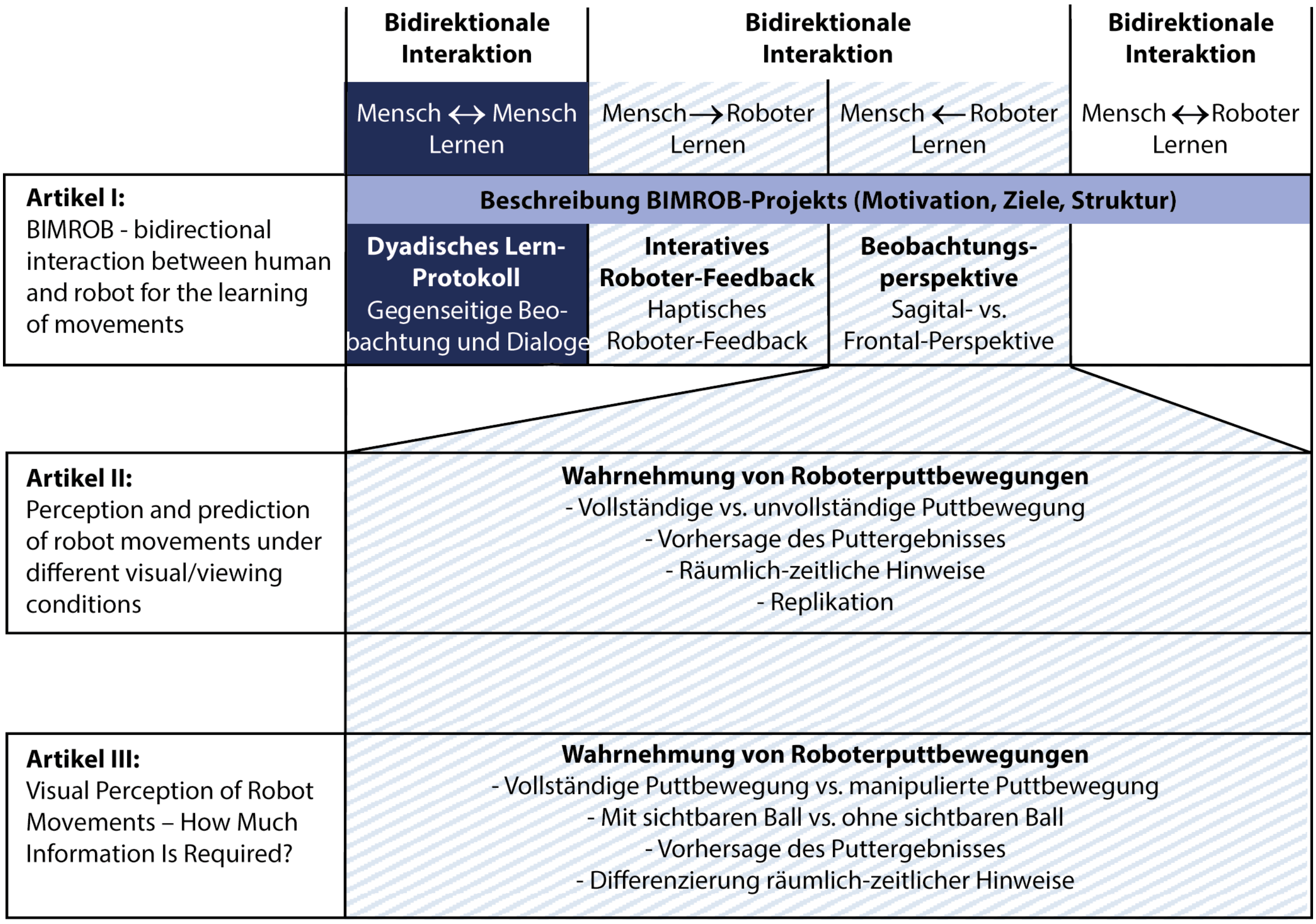

Abbildung 1.3: Flussdiagramm Forschungsprozess und Publikationen.

Aufbauend auf den Erkenntnissen zur Bedeutung der Beobachtungsperspektive geht der zweite Artikel der Frage nach, ob Menschen dazu in der Lage sind, wichtige Bewegungselemente einer Roboterbewegung zu erkennen und eine Leistungsvorhersage zu treffen (Artikel II). Der abschließende Artikel (III) greift die Ergebnisse der beiden Studien aus Artikel II auf und differenziert die wahrzunehmenden Bewegungselemente weiter aus.

Artikel I: BIMROB – bidirectional interaction between human and robot for the learning of movements

Im ersten Artikel werden Struktur und Ziele des BIMROB-Projektes beschrieben. Verdeutlicht wird die Kernidee des Projektes, Erkenntnisse aus den Bereichen des menschlichen und robotischen Bewegungslernens zu verknüpfen und so die wissenschaftlichen Grundlagen für ein verbessertes Training von Mensch-Roboter-Dyaden in unterschiedlichsten Anwendungsgebieten zu erarbeiten. Das Projekt fokussiert sportliche Bewegungen, insbesondere die Puttbewegung im Golf. Verdeutlicht wird die allgemeine Struktur des Projektes, die sich in vier Kernbereiche aufteilt:

1) Das bidirektionale Bewegungslernen von Mensch-Mensch-Dyaden;
2) Das unidirektionale Bewegungslernen eines Roboters von einem Menschen;
3) Das unidirektionale Bewegungslernen eines Menschen von einem Roboter;
4) Das bidirektionale Bewegungslernen von Mensch-Roboter-Dyaden.

Ergänzt wird diese Projektbeschreibung durch die Vorstellung von drei exemplarischen Studien zu den Projektbereichen eins bis drei. Die erste Studie betrachtet die Interaktion beim Bewegungslernen in Mensch-Mensch-Dyaden. Basierend auf den Untersuchungen von Granados (2010) sowie Poolton, Maxwell, Masters und Raab (2006) konnte ein prototypischer, dyadischer Bewegungslernprozess verifiziert werden.

Den Mensch-Mensch-Dyaden wurde die Aufgabe gestellt, je 10 Puttversuche in alternierender Reihenfolge auf einen zwei Meter entfernten Zielpunkt zu absolvieren. Während der eine Proband einen Puttversuch durchführte, wurde dieser vom jeweils anderen Probanden beobachtet. Im Anschluss an die insgesamt 20 Puttversuche der Dyade wurden die Probanden dazu aufgefordert, sich über ihre Erfahrungen und Beobachtungen auszutauschen sowie Verbesserungsmöglichkeiten zu entwickeln. Dieser Versuchsblock wurde sechsmal wiederholt (insgesamt 120 Puttversuche und 5 Dialoge). Die Endposition der einzelnen Puttversuche sowie die Dialoge wurden aufgezeichnet und ausgewertet. Alle Dyaden konnten ihre Puttleistung steigern. Basierend auf den aufgezeichneten Dialogen konnten relevante Themen für den Transfer auf Mensch-Roboter-Dyaden identifiziert werden. Besonders häufig wurden konkret-bewegungsbezogene Aussagen (z. B. Länge, Distanz, Kraft, Schwung, Ausgangsstellung etc.) sowie Meta-Aussagen (z. B. Bewegungskontrolle, Partner, Übungsstrategie etc.) thematisiert. Seltener wurden allgemein-bewegungsbezogene Aussagen (z. B. Leistung und Bewegungsgefühl) und Regelwissen (z. B. Ursache-Wirkung-Beziehungen) genannt.

Den zweiten Strukturbereich repräsentiert eine Untersuchung zur Bedeutung der Beobachtungsperspektive beim Bewegungslernen. Wie von Ishikura und Inomata (1995) beschrieben, nimmt die Perspektive eine wichtige Rolle in der Wahrnehmung von räumlichen Bewegungsinformationen ein. In einem Pre-Test absolvierten die Probanden zwei Tests zur mentalen Rotationsfähigkeit (Dietz, Dominiak und Wiemeyer, 2014), einen Bildkartenauswahltest (BKAT) sowie einen Puttleistungstest auf einen 2 Meter entfernten Zielpunkt. Basierend auf den Ergebnissen des Puttleistungstests wurden die Probanden ad-hoc den drei homogenisierten Versuchsgruppen (Sagittal-, Frontalperspektive und Kontrollgruppe) zugeordnet. Es folgte eine Lernphase, in der die Probanden zunächst mit dem passiv eingestellten Roboter einen Puttversuch durchführten. Im Anschluss nahmen die Probanden die ihnen zugewiesene Beobachtungsperspektive (Frontal- bzw. Sagittal-Perspektive) zum Roboter ein und dieser reproduzierte den zuvor gemeinsam durchgeführten Puttversuch. Den folgenden Puttversuch führten die Probanden wieder gemeinsam mit dem Roboter aus, dieser reproduzierte erneut die initiale Puttbewegung. Die Probanden hatten die Möglichkeit, die Roboterbewegung zu manipulieren bzw. zu verbessern. Basierend auf einem Algorithmus zum inkrementellen Imitationslernen (Ewerton, Maeda, Kollegger, Wiemeyer und Peters, 2016) berechnete der Roboter eine korrigierte Puttbewegung. Dieser Zyklus aus Beobachtung und Korrektur der Roboterbewegung wurde sechsmal durchlaufen. Auf die Lernphase folgte ein Post-Test mit einem Puttleistungstest und einem BKAT. Die Ergebnisse verdeutlichen, dass sich die Puttleistung aller Probanden vom Pre- zum Post-Test verbessert hatten. Die beiden Versuchsgruppen konnten ihre Leistung stärker steigern als die Kontrollgruppe. Im BKAT konnten sich die Probanden insgesamt leicht steigern, es wurden keine Unterschiede zwischen den Gruppen sichtbar.

Abschließend wird eine Untersuchung zur Unterstützung des menschlichen Bewegungslernprozesses durch ein iteratives Roboterfeedback aus dem dritten Strukturbereich vorgestellt. In Abhängigkeit der Reaktionen des Menschen auf das haptische Roboterfeedback wird dieses automatisch angepasst, um den Bewegungslernprozess des Menschen möglichst effizient zu unterstützen. Bisherige iterative Feedbackstrategien (Emken und Reinkensmeyer, 2005) optimierten einzelne Parameter einer spezifischen Bewegung. Der hier verwendete Ansatz bezieht sich dagegen auf beliebige, vollständige Bewegungstrajektorien. In dem verwendeten Lernszenario führt der Roboter den Menschen entlang der zu erlernenden Trajektorie. In den Folgeversuchen soll der Mensch den Roboter entlang dieser Zieltrajektorie führen. Weicht der Mensch von der Zieltrajektorie ab, erzeugt der Roboter ein haptisches Feedback in Form einer Führungskraft. Diese Führungskraft verhält sich proportional zur Abweichung von der Zieltrajektorie. In den folgenden Iterationen wird die Ausprägung des haptischen Feedbacks durch den Roboter an die Reaktionen des Menschen auf das vorangegangene Feedback angepasst. Eine Anpassung des Menschen an die Zieltrajektorie führt zu einem geringen Krafteinsatz des Roboters und umgekehrt. Ohne Abweichung von der Zieltrajektorie werden durch den Roboter keine Führungskräfte erzeugt. Es wird in Anlehnung an Mueller, Brückner, Panzer und Blischke (2001) davon ausgegangen, dass der Mensch das Feedback des Roboters für eine Korrektur in der folgenden Iteration nutzt. In einer experimentellen Untersuchung wurden ein konstantes und ein adaptives Feedback miteinander verglichen. Die Ergebnisse konnten keine Vorteile der adaptiven Feedbackstrategie aufzeigen.

Artikel II: Perception and prediction of robot movements under different visual/viewing conditions

Anknüpfend an die Ergebnisse der im ersten Artikel vorgestellten Untersuchung zum Einfluss der Beobachtungsperspektive (unidirektionales Lernen, der Mensch lernt vom Roboter), erhebt sich die Frage auf, ob Menschen in der Lage sind, wichtige Elemente einer Roboterbewegung wahrzunehmen und das Ergebnis vorhersagen zu können. Die Bedeutung der visuellen Wahrnehmung von Bewegungen in einem bidirektionalen Bewegungslernprozess wurde durch die im ersten Artikel beschriebenen Ergebnisse eines dyadischen Bewegungslernprozesses zweier Menschen deutlich. Bisherige Untersuchungen fokussieren die Beobachtung und Klassifizierung von biologischen Bewegungen (Orgs, Bestmann, Schuur und Haggard, 2011). Runeson und Frykholm (1983) entwickelten das *Kinematics Specify Dynamics Prinzip*, Ballreich (1983) konnte zeigen, dass die kinematischen Eigenschaften einer Sprungbewegung korrekt klassifiziert werden können, Cañal-Bruland und Williams (2010) berichten über den Zusammenhang von distalen Informationen und der Vorhersage der Schlagrichtung im Tennis. Unbeachtet ist bisher die Übertragbarkeit dieser Ergebnisse auf die Wahrnehmung von Roboterbewegungen.

Ziel des Artikels ist zu untersuchen, ob und unter welchen Bedingungen Menschen in der Lage sind, wichtige räumlich-zeitliche Informationen eines Roboterputts wahrzunehmen und eine Vorhersage der Puttleistung zu treffen. In diesem Umfeld werden zwei aufeinander aufbauende Studien vorgestellt. Die erste Studie vergleicht die Wahrnehmung und Leistungsvorhersage unter zwei unterschiedlichen visuellen Bedingungen (vollständige vs. unvollständige Präsentation) von Roboterputtbewegungen über sechs unterschiedliche Distanzen (1.5; 2.0; 2.5; 3.0; 3.5 und 4.0 m). Unter der vollständigen Bedingung werden den Probanden Videosequenzen der vollständigen Puttbewegung (Aushohlbewegung, Anschwungphase und Ausschwungphase) gezeigt. Unter der unvollständigen Bedingung endet die Puttbewegung mit dem Ende der Anschwungphase, dem Treffpunkt von Ball und Schläger. Jede der insgesamt 12 Bewegungssequenzen wird den Probanden viermal in randomisierter Reihenfolge gezeigt. Die Probanden sagen nach jeder Sequenz die Puttdistanz voraus und bewerten die Sicherheit ihrer Entscheidung. Zusätzlich wird die Entscheidungszeit erfasst. Basierend auf dem *Flash-lag effect* wird erwartet, dass mit zunehmender Bewegungsgeschwindigkeit auch der Fehler für die Vorhersage zunimmt (Hubbard, 2014). Aufgrund der zusätzlichen räumlich-zeitlichen Informationen wird ebenfalls erwartet, dass die Vorhersage der Puttleistung unter der vollständigen Sichtbedingung im Vergleich zur unvollständigen Bedingung genauer ist (zeitliche *occlusion*, Loffing und Cañal-Bruland, 2017).

Die zweite Studie baut auf den Ergebnissen der ersten Studie auf, reproduziert diese und erweitert das Studiendesign um zwei zusätzliche manipulierte Sichtbedingungen. Unter diesen beiden zusätzlichen Bedingungen werden der Ball bzw. der Schläger nach dem Treffen des Balls unter der vollständigen Sichtbedingung ausgeblendet (teilweise räumliche *occlusion*; Loffing und Cañal-Bruland, 2017). Die Anzahl der Puttdistanzen wird auf drei (2.0; 3.0 und 4.0 m) reduziert. Den Probanden werden die 12 Sequenzen (3 Distanzen, 4 Bedingungen) jeweils viermal in randomisierter Reihenfolge gezeigt. Die Probanden sagen nach jeder Sequenz die Puttleistung voraus und bewerten die Sicherheit ihrer Einschätzung.

Die Ergebnisse der beiden Studien zeigen, dass es Menschen möglich ist, die Puttleistung eines Roboters vorherzusagen, wenn die vollständige Bewegung gezeigt wird. Dies gilt auch für die manipulierten vollständigen Bewegungen. Eine Leistungseinschätzung basierend auf der unvollständigen Bewegung ist nicht möglich, über alle Distanzen besteht eine Tendenz zur Mitte der Bewertungsskala. Die Sicherheit der Entscheidung unterscheidet sich ebenfalls zwischen der vollständigen und der unvollständigen Bedingung. Daraus kann geschlossen werden, dass insbesondere die Bewegungsphase nach dem Treffen des Balls von großer Bedeutung für die Leistungsvorhersage ist. Die einzelnen räumlich-zeitlichen Hinweiselemente müssen differenziert betrachtet werden.

Artikel III: Visual Perception of Robot Movements – How Much Information Is Required?

Aufbauend auf den Erkenntnissen des zweiten Artikels untersucht diese Studie den Einfluss der Sichtbarkeit einzelner Elemente einer Roboterputtbewegung auf die Qualität der Vorhersage der Puttleistung durch die Probanden. Während im zweiten Artikel gezeigt werden konnte, dass Menschen in der Lage sind, bei der Beobachtung einer vollständigen Roboterputtbewegung die Puttleistung vorherzusagen, konnte nicht geklärt werden, welche Elemente oder Kombinationen von Elementen der Bewegung (Roboter, Ball, Schläger, radiale Distanz zwischen Schläger und Ball etc.) für die Beurteilung der Bewegung genutzt werden. Diese Fragestellung wird im dritten Artikel untersucht.

Es wird vermutet, dass insbesondere die Sichtbarkeit des Balls und die daraus resultierenden zusätzlichen und teils redundanten räumlich-zeitlichen Informationen (z. B. radiale Distanz zwischen Schläger und Ball, Geschwindigkeit von Schlägerkopf und Ball) einen positiven Effekt auf die Vorhersage der Puttleistung besitzen. Insgesamt werden sechs unterschiedliche Bedingungen über jeweils drei unterschiedliche Distanzen der vollständigen Bewegung eingesetzt. Dies sind teils manipulierte Varianten der vollständigen Bedingung mit den folgenden sichtbaren Komponenten:

1) Roboter, Schläger, Schlägerkopf und Ball (vollständige Bedingung);
2) Roboter, Schläger und Schlägerkopf ohne Ball;
3) Schläger, Schlägerkopf und Ball;
4) Schläger und Schlägerkopf ohne Ball;
5) Schlägerkopf und Ball;
6) Schlägerkopf ohne Ball.

Den drei Versuchsgruppen wurden unterschiedliche Kombinationen von jeweils zwei Bedingungen mit und ohne sichtbaren Ball präsentiert.

Die Ergebnisse bestätigen die bisherigen Erkenntnisse, Menschen können bei einer ausreichenden Informationsdichte die Leistung einer Roboterputtbewegung vorhersagen.

Die Sichtbarkeit des Balls ist dabei von großer Bedeutung. Unter den Bedingungen mit sichtbaren Ball konnte die Puttleistung besser vorhergesagt werden als in den Bedingungen ohne sichtbaren Ball.

Die Ergebnisse müssen im Hinblick auf das verwendete Studiendesign jedoch kritisch betrachtet werden. Den drei Versuchsgruppen wurden jeweils nur die Sequenzen unter vier Bedingungen (zwei unterschiedliche Bedingungen mit und ohne sichtbaren Ball) gezeigt. Eine Auswertung konnte daher nur innerhalb der einzelnen Gruppen erfolgen. Ein direkter Vergleich aller Bedingungen ist nicht möglich. In weiteren Untersuchungen sollten den Probanden die Sequenzen aller Bedingungen gezeigt werden.

Zum Zeitpunkt der Einreichung dieser Arbeit wurden zwei der verwendeten Arbeiten veröffentlicht (Artikel I und III), die dritte Arbeit wurde eingereicht und befindet sich im Reviewprozess (Artikel II). Alle Publikationen wurden in englischer Sprache verfasst und werden im Folgenden auch in Englisch dargestellt. Aus Gründen der Vereinheitlichung wurden die Bezeichnung der unterschiedlichen Versuchsbedingungen, der Zitationsstil, die Bezeichnung und Beschriftung von Tabellen und Abbildungen sowie Schriftgröße und Schriftart in den Abbildungen der drei Artikel angepasst. Aus Übersichtsgründen wurden mehrere Tabellen aufgeteilt. Inhaltlich wurden keine Änderungen vorgenommen.

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2 Artikel I: BIMROB–bidirectional interaction between human and robot for the learning of movements

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2.1 Introduction

Over the last 50 years, robots have become indispensable in many application fields, e.g., in the car industry, rehabilitation and training. Currently, a paradigm shift is taking place from “classical” robots, which have been rigidly programmed towards a new, more adaptive type that is capable of learning. This new paradigm of common learning of humans and robots has huge potential for changing sensorimotor training in sports and rehabilitation. However, learning robots are still at an early stage of development. Their interaction with humans has been poorly understood and the dynamics resulting from humans learning tasks jointly with robots have not yet been deeply explored. The core idea of the Bidirectional Interaction between Human and Robot when learning movements project[1] is to combine the insights from the fields of human and robotic learning to lay the scientific foundations for improved training in human-robot dyads in various application fields, with a particular focus on sport movements. The purpose of this paper is to describe the project’s objectives in general and to present selected experiments addressing important issues of human-robot learning.

2.2 Project description

The main objective of the Bidirectional Interaction between Human and Robot when learning movements project is to study the bidirectional interaction of humans and robots when learning movements aiming for finding their best configurations for both effective and efficient dyadic sensorimotor learning. Therefore, we address the unidirectional transfer from humans to robots or from robots to humans first, followed by their bidirectional interaction in dyad learning. This procedure results in four settings (see Fig. 2.1).

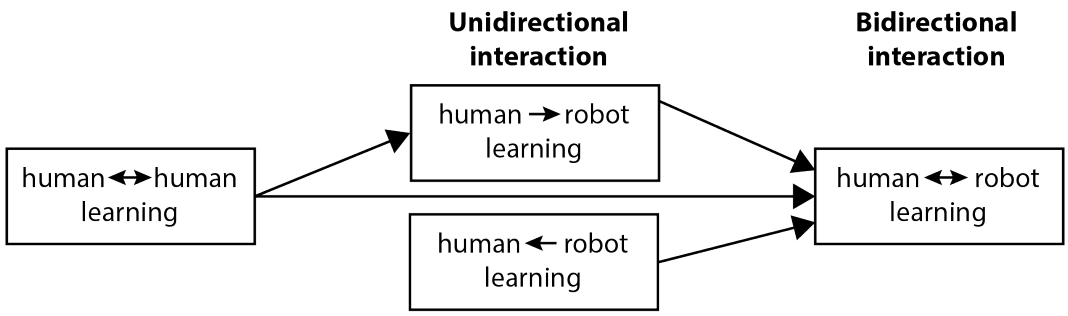

Figure 2.1: Structure of the BIMROB project – four basic settings.

The first task in the Bidirectional Interaction between Human and Robot when learning movements-project was to establish the technical prerequisites. These are described in the following sections. Following this description, three exemplary studies are presented for the settings of human-human learning and unidirectional human- robot learning.

2.2.1 BioRob system

The technical platform for the Bidirectional Interaction between Human and Robot when learning movements project is a BioRob robotic arm (see Fig. 2.2).

[1]Forum for Interdisciplinary Research (FiF) at the Technische Universität Darmstadt (www.fif.tu-darmstadt.de).

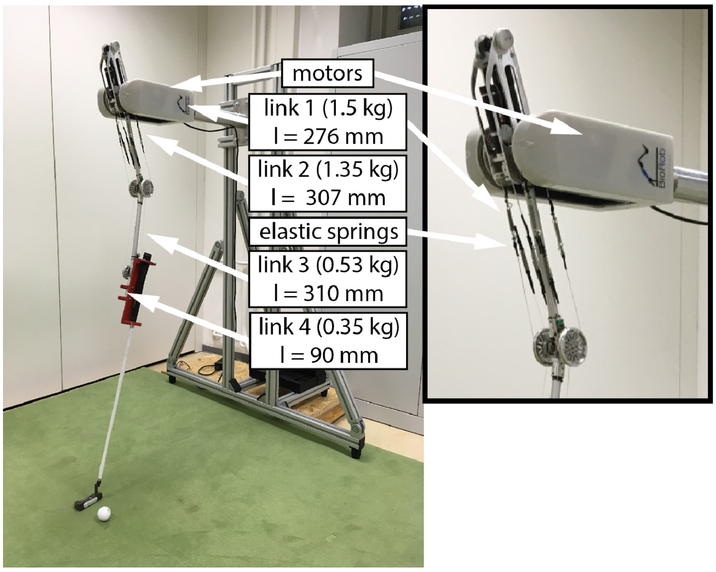

Figure 2.2: BioRob with 4 DoF on a movable lightweight frame construction for experiments.

This robotic system has been developed for the direct physical interaction between humans and robots. The system has four elastically actuated joints. Each joint is controlled by a motor located in the base. Each motor is coupled with four built-in elastic springs. Because of its lightweight design, the BioRob, which only generates little kinetic energy, is safe to use without collision detection even in high speed physical human-robotinteractions (Ballreich, 1983; Lens, Kunz, Von Stryk, Trommer, and Karguth, 2010). In order to position the BioRob arm freely and/or to adapt it to individual anthropometric parameters human participants, a special lightweight frame has been developed (see Fig. 2.2). This allows for simple height adjustments as well as free positioning of the robot arm.

2.2.2 Artificial putting green

To study the interaction of robot and humans, we have constructed an artificial putting green. It is two meters wide and six meters long. Twelve aluminum profiles (1x1 m) were combined and covered by a carpet, whose properties are suitable to resemble putting (see Fig. 2.3). This design allows for the BioRob to be positioned freely on its base and human participants to move all over the green.

Video cameras located above the putting green (see Fig. 2.3), are used to detect the final position of the ball after each trial. Prospectively, an automatic real-time ball detection will be developed allowing predictions about the ball's trajectory and its final position.

2.3 Human-human-interaction – A dyad learning protocol

The first setting of the project considers the human-human interaction in motor learning. Therefore, the aim of this exploratory experiment was to develop an experimental design for dyadic learning and to identify topics addressed in human-human dyads (for a detailed description, see Kollegger, Ewerton, Peters, and Wiemeyer, 2016).

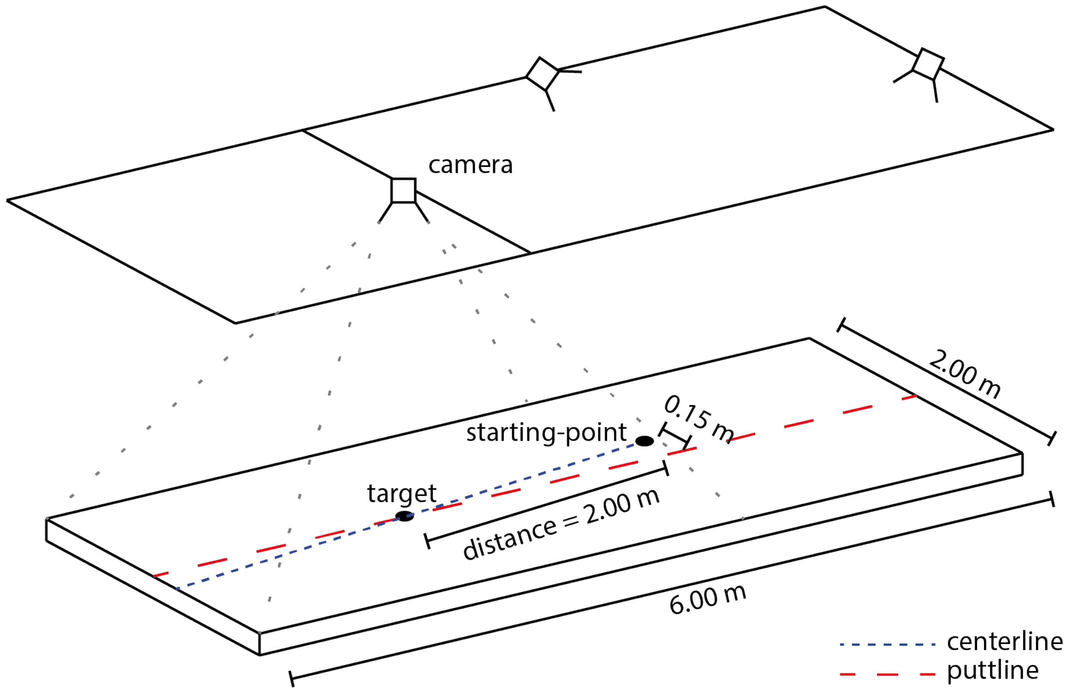

Figure 2.3: Schematic illustration of the artificial putting green with cameras for the detection of final ball position, target and starting point, centerline as well as putt line.

2.3.1 Sample

24 Students (12f, 12m) participated in the experiment. Inclusion criteria were that they had no previous experience in golf. Participants were assigned to three different types of dyads based on their gender: female-female, female-male and male-male.

2.3.2 Task and procedure

The Task was to putt towards a target located at a distance of two meters. In the dyads, participants practiced the golf putt (60 trials) in alternating order (120 putts per dyad). For example, while participant A performed his trials, participant B observed and vice versa. After every 20 trials per dyad, the pairs of participants were engaged in a dialog about their experiences(Kollegger et al., 2016).

2.3.3 Data analysis and processing

The radial distance to the target was calculated based on video recordings. All 60 dialogues (five per dyad) were also recorded with a video camera. Recordings were transcribed and analyzed using qualitative content analysis. Performance data were analyzed by two-factor ANOVA with repeated measures. In case of sphericity violation e corrections were applied. The level of significance level was set a priori to 0.05.

2.3.4 Results

Putt performance, i.e., radial distance to the target, shows significant improvements over six blocks (F(3,72), p=.028, η_p^2 = .121). In the verbal reports, 867 statements were identified which could be classified into four main categories: concrete movement- related aspects (e.g., direction, distance, posture, grip, and oscillate), meta-statements (e.g., partner, exercise strategies and movement control), general movement-related statements (e.g., performance and movement sensations) and cause-effect relationships (e.g., if-then rules). In all dyads, references to the learning material were made, particularly to handle, posture and head position.

2.3.5 Discussion

On the one hand, the developed experimental setup was verified. On the other hand, important topics relevant for human-robot interactions were identified.

2.4 Human-robot learning – Observation perspective

The second setting (see Fig. 2.1) considers the unidirectional human-robot interaction in motor learning: How can humans learn from robots? When learning movements, the perspective of observation plays an important role in the perception of different spatial movement information (Ishikura and Inomata, 1995). In addition, mental rotation is required to transform the movement observed from an external perspective into an ego perspective. The study presented here examines the influence of the observational perspective on human movement learning in human robot dyads. According to Ishikura and Inomata (1995), we had expected advantages for the frontal over the sagittal perspective.

2.4.1 Methods

Participants

32 persons (14 female, 18 male) participated in the experiment. Inclusion criteria were no previous experiences in golf, field hockey or ice hockey. All participants gave informed written consent prior to the study. The age ranged from 15-35 years (mean 25.7±4.1 years). Participants were assigned ad-hoc to three different groups based on their putt performance in the pre-test (see Table 2.1).

Table 2.1: Anthropometric data of participants and experimental groups with putt performance of the pre-test.

Condition/Perspective	n	Gender [m/f]	Age [years]	Putt performance (pre-Test) [cm]
Sagittal perspective	11	6 / 5	26.0±2.7	46.5±39.0
Frontal perspective	11	7 / 4	27.9±3.7	47.4±44.4
Control	10	5 / 5	22.9±4.3	46.3±36.0
Total	32	18 / 14	25.4±4.7	46.8±38.1

Apparatus and Task

The experiment was performed on an artificial putting green (see Fig. 2.3). Participants' task was to hit standard golf balls (BEAST, Lady) with a standard golf putter (MacGregor DX) attached at the end-effector of the BioRob (see Fig. 2.4), towards a target located two meters from the starting point. The starting point was located 15 cm aside from the center line to the right, while the target was located on the center line of the putting green (Poolton et al., 2006; see Fig. 2.3).

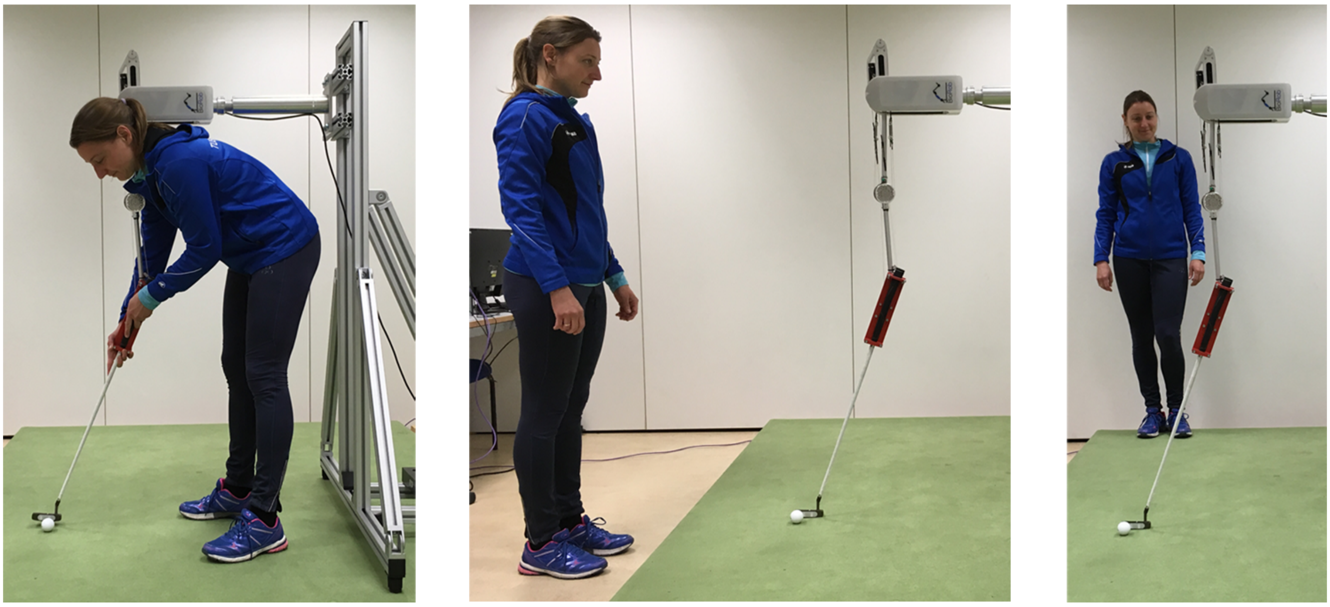

Figure 2.4: Putting participant with a putter attached at the end-effector of BioRob (left) and observation perspectives (center: frontal; right: sagittal).

Procedure

All participants received written information about the procedure and completed a pretest consisting of seven unconstrained putt trials, i.e., putter was not attached at the BioRob, two different mental rotation tests (MRT; MRT-Peters and & MRT-Bio; Dietz et al., 2014) and two different picture selection tests (PSTs). Based on their putt performance in the pretest, participants were randomly assigned to the three experimental groups. After the pretest, the frontal and sagittal groups completed a training phase of seven trials. The putter was attached to the end-effector of the robot arm (see Fig. 2.4). During the initial trial the BioRob was not actuated and just recorded the movement trajectory. After this first trial, participants took the assigned observation perspective (see Fig. 2.4) and the robot replicated the putt performed by the participant. In the next trial, the putt was again replicated by the robot, and the participants had the possibility to actively correct the putting movement of the robot and to change the trajectory. This sequence of observation and correction was repeated six times. The no-treatment control group did not perform putts with the robot; instead, the participants were shown an information video about the BioRob. After the training phase, all participants completed a post-test (putt performance and PST). The final position of the ball was recorded with a video camera located above the target point. Based on the video, the radial distance to the target was calculated for each trial in the pre- and post-test and also in the training phase.

Data analysis

Putting performance and PST data were analyzed by a two-factor MANOVA with repeated measures using SPSS (v24). The mental rotation tests (MRTs)s were examined for group differences with a univariate ANOVA. The level of significance level was set a priori to 0.05.

2.4.2 Results

All participants improved their putt performance from the pretest to the posttest, however, the difference was just above the level of significance (F(1,19)=4.12, p=.052, η_p^2=.12). Interaction of group and test was not significant indicating no learning advantages for any group (F(2,29)=0.45; p=.64; η_p^2=.03). However, the training groups achieved a much stronger mean improvement (frontal group +17.1 % and sagittal group +22.8 %) than the control group (+5.5 %; see Fig. 2.5). No effects of perspective were found for PST (F2,29=.022, p=.98) and MRT-Peters (F2,29=2.03, p=.150) but for MRT-Bio (F2,29=3.551, p=.042, h2 p=.197). Follow-up analyses (U-test) revealed a significant difference between the frontal group and the control group.

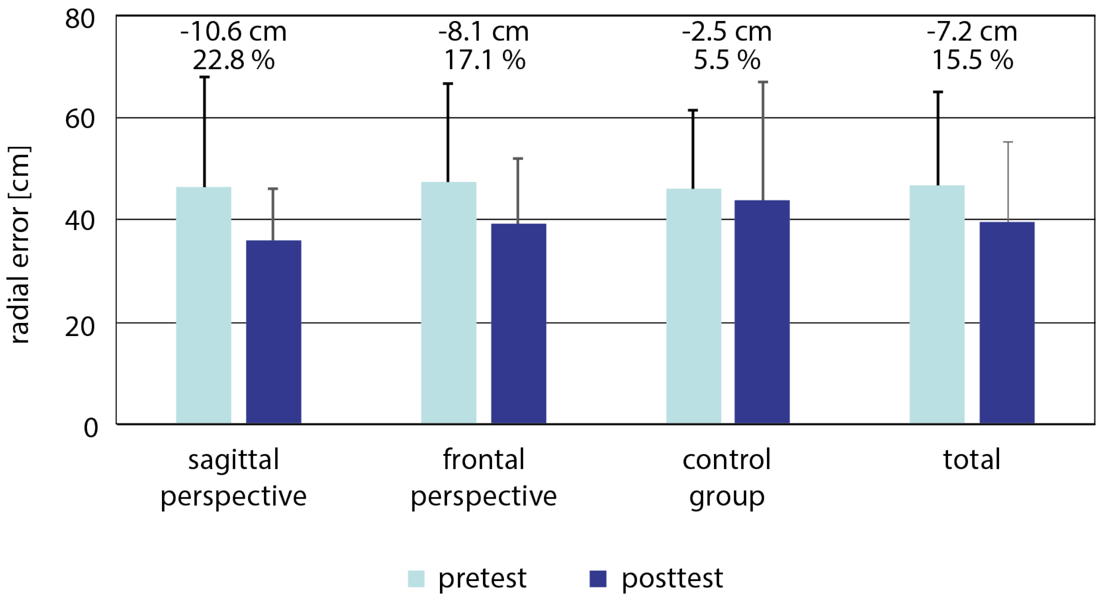

Figure 2.5: Putt performance as radial distance from the target in the pretest and posttest.

2.4.3 Discussion

This study does not confirm the above-mentioned superiority of the frontal perspective. There are several possible reasons for this result: First, the study was underpowered ($1 - \beta = 0.38$). For detecting an effect size of 0.03, a total sample of 81 would have been required. Second, the study included switching between free putting in the pre- and posttests and constrained putting in the training phase in the treatment groups. This switching may have caused confusion in the treatment groups. Third, the training phase comprising seven trials may have been too short to find a clear training effect. Fourth, a more detailed analysis provided some hints that the participants adopted different strategies depending on the observation perspective. The participants of the frontal group seem to have tried to correct the movements of the robot based on the observed robot putt, whereas the participants of the lateral group seem to have focused on their own movements when correcting the robot movements.

In future studies, we plan to circumvent these issues by including a larger sample, more acquisition trials, and to avoid switching between free and constrained putting. Furthermore, the inclusion of a further training condition without observation and feedback is promising.

2.5 Human-robot learning - Iterative robot feedback

Part of our previous work focused on finding ways to transfer motor skills from humans to robots. For instance, through demonstrations of interactions between a human and a robot, it was possible to teach the robot how to assist a human partner in a box assembly task (Ewerton, Neumann, et al., 2015). Further developments to this algorithm enabled the robot to learn motor skills from partially observed demonstrations executed at different speeds (Ewerton, Maeda, Peters, and Neumann, 2015). Moreover, the robot was able to optimize the speed of execution of movements taught by demonstrations (Ewerton, Maeda, Neumann, et al., 2016) and to learn from incremental human feedback (Ewerton, Maeda, Kollegger, et al., 2016). In this section, an approach is presented that explores transferring motor skills in the opposite direction, i.e. from robots to humans, with possible implications for sports and rehabilitation.

2.5.1 Introduction

Emken and Reinkensmeyer (2005) developed an iterative method that helps humans to achieve specific goals such as a pre-defined maximal foot height during the swing phase of walking. This method optimizes only a single parameter, rather than entire trajectories. In our work, we try to overcome this limitation by investigating how robots can help humans to learn movement trajectories through iterative feedback-based strategies. The basic idea is to adjust the correction strategy of the robot according to the estimated sensitivity of the human in order to optimize human motor skill learning. In the following, our proposed correction strategy of the robot, which allows for adjustments in the human's reaction, is presented. Afterwards, experiments in which humans practice a motor skill with the assistance of the BioRob (see Section 2.1) are presented. Finally, the experimental results and ideas for future work are discussed.

2.5.2 Feedback strategy

A method was developed to teach arbitrary trajectories to humans with the help of a robot (see Fig. 2.7): First the robot guides the human along a pre-defined reference trajectory τ_H^{des} During this phase, the force F_k applied by the robot increases in proportion to the deviation from the reference trajectory $(\tau_H^{des} - \tau_H^k)$ (iteration k, see Fig. 2.6):

$$F_k \propto \beta \cdot (\tau_H^{des} - \tau_H^k)$$

The parameter β determines how strong the robot's feedback is, given a deviation from the reference trajectory. For positive or negative β values, the robot applies a force in the direction of $(\tau_H^{des} - \tau_H^k)$ or in the opposite direction, respectively. For example, if $\beta < 1$, the robot tends to apply less forces in proportion to the actual deviation (in case of high sensitivity of the human). On the other hand, if $\beta > 1$, the robot tends to apply higher forces, compensating for the low sensitivity of the human.

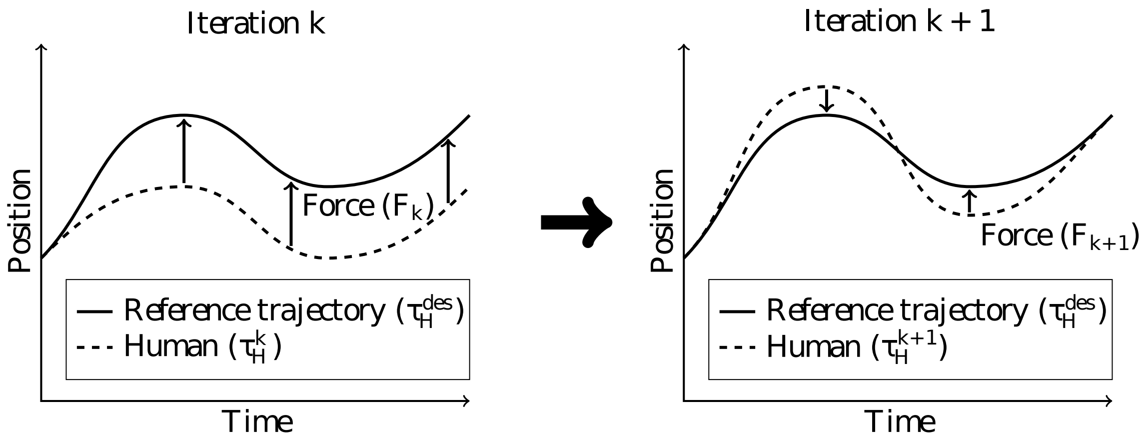

Figure 2.6: Iterative method for motor skill learning in human-robot dyads. The force applied by the robot depends on the difference between the executed trajectory and the reference trajectory as well as on the estimated sensitivity of the human to the robot's feedback. It is assumed that the human's sensitivity can be estimated from a change in the executed trajectory from iteration k to iteration $k+1$ and that this change is proportional to the robot's forces in iteration k.

Through the robot's guidance, the human receives a haptic information about the trajectory to be learned. In the next iteration (iteration $k+1$, see Fig. 2.6), the task for the human is to move the robot along the reference trajectory τ_H^{des}, to feel as little guiding forces by the robot as possible, probably resulting in a low deviation from the reference trajectory. If the human follows exactly the reference trajectory, he or she will not feel any guiding force by the robot. The trajectory τ_H^{k+1} executed by the human is recorded by the robot and is compared to the trajectory τ_H^k executed in the previous iteration in order to estimate the human's sensitivity. As a result, the robot's haptic feedback in the next iteration (iteration $k+2$) depends on the estimated human sensitivity. A high estimated sensitivity leads the robot to apply less force and vice versa. This iterative method starts from the assumption that the human uses the robot's correction forces, possibly with a damping or amplification factor, directly for the correction of the next movement:

$$\tau_H^{k+1} \propto \tau_H^k + \alpha \cdot F_k = \tau_H^k + \alpha \cdot \beta \cdot (\tau_H^{des} - \tau_H^k)$$

This equation is compatible with the model of Mueller et al. (2001). The parameter α determines the human's reaction to the robot's feedback. For positive or negative α values, the human changes the trajectory according to or opposite to the robot's feedback, respectively. In addition, low or high α values indicate low or high sensitivity of the human to the robot's feedback. By choosing $\alpha = \beta = 1$, the robot's feedback exclusively depends on the deviation from the desired trajectory, i.e., without considering the sensitivity of the human (baseline strategy; BL). If the robot estimate the sensitivity parameter α and β is computed such that $\alpha \cdot \beta = constant$, the robot adapts its feedback to the sensitivity of the human (adaptive strategy; adap.). The parameters α and β can be computed with linear regression.

2.5.3 Experimental procedure

Exploratory experiments with four participants (two males, two females, age ranging from 24-34 y) were conducted. The trajectory to be learned in these experiments corresponds to an arch-shaped movement from the middle to the left, to the right and back to the middle (see Fig. 2.7). Two participants trained using the baseline strategy, while the two other participants trained using the adaptive strategy.

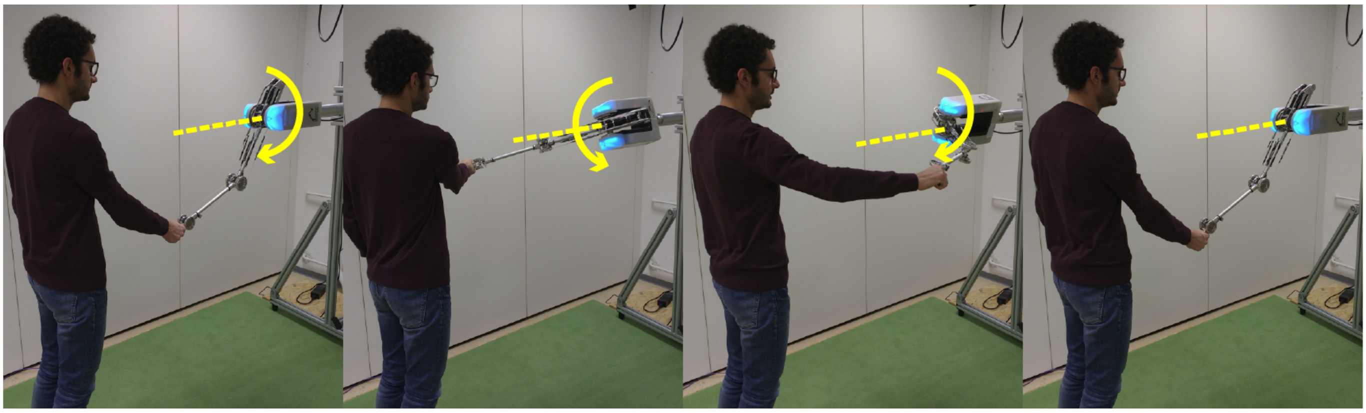

Figure 2.7: Movement to be learned by the human with the assistance of the robot: arch-shaped movement from the middle to the left, to the right and back to the middle.

In all iterations during training, the robot's controller compensates for its weight. The controller detects the robot's joint angles with a resolution of less than 0.5 degree and computes the motor commands with a frequency of 500 Hz. For each participant, the workflow of the experiment (see Fig. 2.8) was as follows:

ten training iterations with the baseline or with the adaptive method, five iterations with no feedback (early retention), ten minutes playing computer games and finally five iterations with no feedback (delayed retention). For the adaptive condition, $\alpha \cdot \beta = 0.5$.

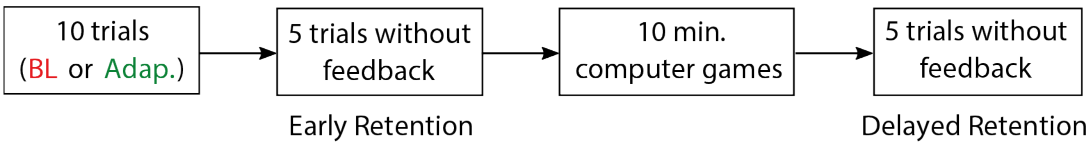

Figure 2.8: Workflow of experiments.

2.5.4 Results and discussion

Fig. 2.9 and Fig. 2.10 show the RMSE between actual and desired trajectory of joint one (most relevant joint for the movement in this experiment; see Fig. 2.7) of the robot being manipulated by the human without and with time-alignment, respectively. The time-alignment was performed with dynamic time warping (Sakoe and Chiba, 1978). During training, the feedback given by the robot helps maintaining a low RMSE.

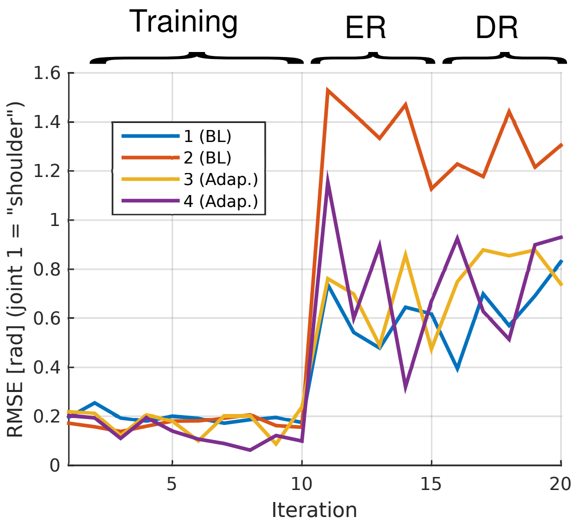

Figure 2.9: Root-mean-square error between actual and desired trajectory of joint 1 of the robot being manipulated by the human (without time-alignment).

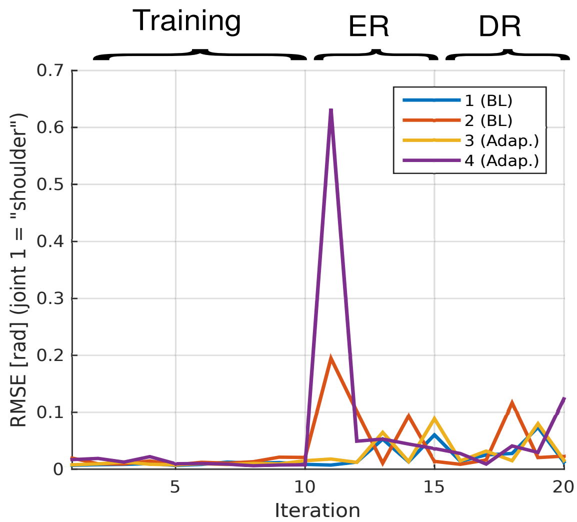

Figure 2.10: Root-mean-square error between actual and desired trajectory of joint 1 of the robot being manipulated by the human (with time-alignment).

In the early retention (ER) and delayed retention (DR) phases, the RMSE is higher due to the absence of feedback. In addition, most of the error is due to the misalignment in time between the trajectories the participants executed and the desired trajectory. The plots show no conclusive difference between the errors made by participants after training with the baseline and with the adaptive method.

Fig. 2.11 shows the computed values of the parameter α for the two participants who trained with the adaptive method. In these experiments, the values of the parameter α oscillate considerably from one iteration to the next, which results in oscillating values of the parameter β leading to inconsistent feedback by the robot. This difference in the intensity of the feedback from one iteration to the next might have caused confusion in the participants. Thus, it may be worth updating β not for every iteration, but only a certain number n of iterations.

2.5.5 Conclusion

We proposed an iterative feedback-based correction strategy to teach motor skills to humans with the assistance of a robot. In our method, the robot is able to adapt its feedback to the estimated sensitivity of the human. Moreover, a baseline approach with no adaptation can be considered as a special case of our method.

The exploratory study could not confirm an advantage of the adaptive strategy. Future work will explore variations of this strategy in which the robot does not adapt its feedback at every iteration, but after a number of iterations, potentially computing a better estimate of the sensitivity of the human.

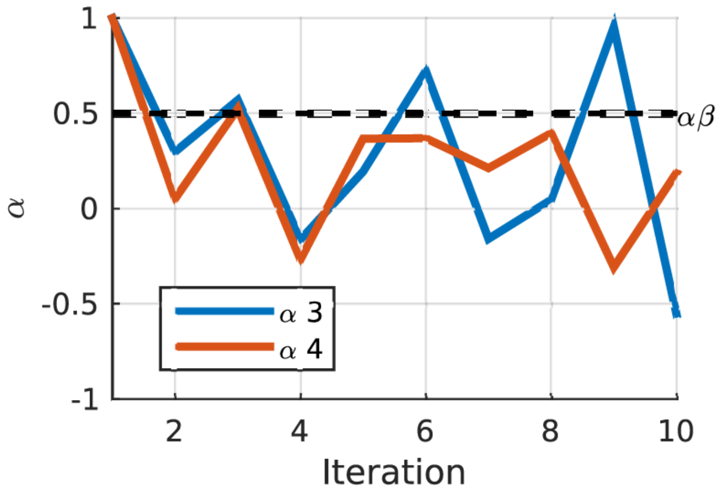

Figure 2.11: Computed values of parameters α for participants 3 and 4, who trained with the adaptive method. These values show a large oscillation.

2.6 Conclusion

First, the feasibility of the developed platform (BioRob system and artificial putting green) was confirmed. The robot system was able to perform and imitate the required putting movement with reasonable accuracy. The light-weight positioning system allows for adequate location of the robot. Furthermore, the studies performed so far provide important insights into both human- human interaction and unidirectional human-robot interaction when learning putting movement. Observation conditions (e.g., video length and perspective) as well as robot learning from demonstrations and incremental human feedback and algorithms for robot support of human learning revealed results that will be included in further studies of bidirectional interaction of robots and humans. For example, several strategies of learning (e.g., focus of attention, error correction, and feedback processing) were uncovered in the studies. In future studies, the study of bidirectional human-robot interaction will focus on combining the advantages of both human and robot learning. The aim is to find adequate procedures including phases of self-optimization of humans and robots as well as phases of humans teaching robots and robots teaching humans (Schmidt and Lee, 1988).

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3 Artikel II: Perception and prediction of robot movements under different visual/viewing conditions

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Zur Veröffentlichung eingereichter Artikel in *PlosOne*

3.1 Abstract

The purpose of this paper is to examine, whether and under which conditions humans are able to predict the putting distance of a robotic device. Based on the "flash-lag effect" FLE it was expected that the prediction errors increase with increasing putting velocity which is necessary to achieve different putting distances (Hypothesis 1). It was expected that the predictions are more accurate and more confident if human observers operate under full vision (F-RCHB) compared to either incomplete vision (I-RCHB; Hypothesis 2: temporal occlusion) or to limited vision after impact, i.e. invisible ball (F-RHC) or club (F-B; partial spatial occlusion; hypothesis 3). In two studies, 48 video sequences of putt movements performed by a BioRob robot arm were presented to thirty-nine students (age: 24.49±3.20 years, height: 175.82±8.50 cm, body mass: 72.15±11.78 kg). In study 1, video sequences included six putting distances (1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m) under full versus incomplete vision (F-RCHB versus I-RCHB) and in study 2 three putting distances (2.0, 3.0, and 4.0 m) were presented under the four visual conditions (F-RCHB, I-RCHB, F-RCH, and F-B). After the presentation of each video sequence, the participants estimated the putting distance on a scale from 0 to 6 m and documented their confidence of prediction on a 5-point scale. Both studies show comparable values for the respective dependent variables (error measures and confidence). The participants consistently overestimated the putting distance under the full vision conditions; however the estimation did not show a pattern that was consistent with the FLE. Under the incomplete condition, a prediction was not possible; rather a random estimation pattern was found around the centre of the prediction scale (3 m). Spatial occlusion did not affect errors and confidence of prediction.

3.2 Introduction

Human-robot interaction is gaining importance due to the increasing penetration of many areas by robotic devices, e.g., in rehabilitation, industrial production and motor skill learning in sports. The overlap of operating spaces between robots and humans is constantly growing. In this regard, an important question is how robots and humans can cooperate in an effective way. In an ideal cooperative scenario the perceptions and actions of humans and robots are perfectly coordinated taking the best of both, i.e., accuracy and precision of robot movements and flexibility and adaptability of human perception and action. This human-robot coordination has to be learned on both sides. Therefore, this paper focuses on motor skill learning of robot-human dyads. The learning of humans and robots raises numerous questions. For example, if and under which conditions can robots profit from humans and vice versa. One possible scenario may be that at the beginning of the learning process humans teach robots by showing them a first solution and correcting big errors. After this initial phase of acquiring a rough solution (movement topology; Blischke, Marschall, Muller, and Daugs, 1999) the robot may self-optimize its motions and may come up with solutions that are of value for the human. Taking the example of putting motion, the human guides the robot's first attempts to hit the ball and approach the hole. The human teacher watches and corrects the motions if necessary. As soon as the robot motion has gained sufficient structural stability, a phase of self-optimization will follow. Finally, the robot presents its motions to the human who may use this information as visual or haptic guidance to improve her or his own putting (model or parameter learning; Blischke et al., 1999). In this hypothetic scenario, watching the robot motions plays an important role for the human to identify the relevant information in order to guide his or her own motion. Therefore, the question arises to what extent humans are able to perceive and predict robot motions.

In this paper, the issue of human perception of robot movements is addressed by two experiments where humans perceive and predict video-taped putting motions performed by a robot. Humans are able to perceive motions in several ways by monocular or binocular vision from dynamic and static input (Blake and Shiffrar, 2007; Orgs et al., 2016). One perceptual strategy is to keep the eyes still and let the moving object pass (afferent motion perception, Dichgans, Wist, Diener, and Brandt, 1975). In this case, the brain constructs motions by integrating the successive projection of light on different retinal locations. This option is appropriate for the detection of motion, particularly in the periphery of the retina. However, due to the low visual acuity outside the fovea centralis, this strategy does not allow for identifying details of the moving object. As a consequence, velocity of a single moving object tends to be overestimated (Dichgans et al., 1975). Respective experiments in psychophysics show, that the ability to discriminate velocity differences follows a U-shaped function favoring velocities of 8 to 64 degrees per second with a sensitivity threshold of about 5% for velocities over 2 degrees per second (Orban, de Wolf, and Maes, 1984).

Another option allowing for more visual acuity and more accurate perception is to track the object with the eyes (efferent motion perception). In this case, the retinal location of the moving object is more or less stable and the impression of motion is elicited by integrating foveal and peripheral vision and proprioceptive feedback as well as control signals to the eye muscles. However, this second type of motion perception is limited to low object velocities, as object velocities beyond 70 degrees per second require saccadic eye movements (Dichgans et al., 1975).

Numerous experiments confirm that humans are able to perceive and classify biological movement, even if only few stimuli are available ("structure-from-motion studies", Orgs et al., 2011). Furthermore, the human system for visual perception of motion seems to be hierarchically organized (Gershman, Tenenbaum, and Jäkel, 2016; Giese and Poggio, 2003). In the point-light approach (review: Blake and Shiffrar, 2007) introduced by Johansson (1973), for example, human observers are able to judge the gender and identity of acting persons (Cutting, 1978; Cutting and Kozlowski, 1977), the weight of lifted boxes (Bingham, 1987, 1993; Runeson and Frykholm, 1981), specific motor actions like gait (Lappe, Wittinghofer, and de Lussanet, 2015) and even emotions, intentions and attempted deceptions (Runeson and Frykholm, 1981). Based on these results, Runeson and Frykholm (1983) proposed the principle of "Kinematics Specify Dynamics" (KSD principle). The KSD principle claims that "movements specify the causal factors of events" (Runeson and Frykholm, 1983, p.585). However, human ability to perceive motions seems to be limited to nominal and ordinal judgement, i.e., classification and ranking. In a preliminary study, Ballreich (1983) found that 29 expert coaches in jumping were able to rank kinematics (i.e., duration and velocity) and kinetics (i.e., force) but not joint angles of three successive high jumps. Cañal-Bruland and Williams (2010) report evidence that distal cues, e.g. motion of the racquet, play an important role in predicting the directions of tennis strokes. The perception of human motion is subject to numerous influencing factors comprising features of the moving object (e.g., velocity, trajectory, size, and distance) and the observer (e.g., perceptual-motor experience, knowledge, and object-observer relation). An open question is whether the results found for biological motion transfer to non-biological motion. Recent evidence, both psychological and neurophysiological, suggests an interaction of distinct pathways processing biological and non-biological motion (Hegele, 2009; Lu, Li, and Meng, 2016). Interestingly, the perception of animate motion can be elicited by simple visual stimuli with specific changes in velocity and direction (Tremoulet and Feldman, 2000). Whereas the proposed experimental evidence confirms the hypothesis that kinematic parameters are integrated in the visual system to elicit nominal and ordinal judgements, it is unclear how well humans can estimate kinematics on a metric scale. The quantitative judgement of movements appears to be subject to numerous sources of error (Dichgans et al., 1975; La Scaleia, Zago, Moscatelli, Lacquaniti, and Viviani, 2014). For example, the "flash-lag effect" (FLE) indicates that the visual system commits errors when predicting the future position of moving objects (Hubbard, 2014; Nijhawan, 2002). The FLE shows that under certain conditions humans tend to systematically overestimate the future position of moving objects. In soccer, for example, this perceptual error leads to a large number of false flags (offside Baldo, Ranvaud, and Morya, 2002). The FLE is subject to numerous influences (review: Hubbard, 2014), for example, velocity of visual target, eye movements (Kerzel, 2003b), attention (Kerzel, 2003a) level of expertise, learning, and training (Witt, 2011), motion type, motion context (Kerzel, 2003b), and expected dynamics (La Scaleia et al., 2014). Studies in neurosciences confirm an important contribution of area MT+ (medium temporal cortex) to the FLE (Maus, Ward, Nijhawan, and Whitney, 2012), an area which is also involved in the perception of motion in general (Perani et al., 2001) and especially regarding motion direction (Giese and Poggio, 2003; Rodman and Albright, 1989). There are numerous theories trying to explain the FLE (for a review, see Hubbard, 2014). The purpose of this paper is to examine, whether and under which conditions humans are able to predict the putting distance of the putting motions of a robotic device. Due to the FLE it is expected that prediction errors increase with increasing putting velocity which is necessary to achieve different putting distances (hypothesis 1). Furthermore, the influence of watching different proportions of motion (temporal occlusion paradigm; Loffing and Cañal-Bruland, 2017) as well as different vision conditions (spatial occlusion paradigm) is tested. It is expected that predictions are more accurate, more confident and faster if the human observers watch the full vision condition compared to the incomplete vision condition (temporal occlusion; hypothesis 2). In addition, it is expected that predictions are more accurate, more confident and faster with full vision (i.e. robot, club, and ball) compared to restricted vision after the impact, i.e., invisible ball or club (partial spatial occlusion; hypothesis 3; Loffing and Cañal-Bruland, 2017).

In the following, two consecutive studies are described. In the first study, different movement sequences were presented at six different distances. Based on the results of the first experiment, the second study aimed at replicating the results of the first study and additionally manipulating the amount of information (visibility of club and ball in full vision condition).

3.3 Study 1 – Full vs. incomplete vision condition

In this study, hypothesis 1 and 2 are addressed by applying the temporal occlusion paradigm. Video sequences of robot putts at six different distances are presented to the participants. For each distance, videos are shown under two different visual conditions, i.e. full vision condition with visible robot, club, club head, and ball (F-RCHB)[1], including preliminary, backswing, downswing, and follow-through phase, and incomplete vision condition with visible robot, club, club head, and ball (I-RCHB) including preliminary, backswing, and downswing phase until the club-ball impact (Note: The abbreviations are introduced here to make it easier to understand the abbreviations for the second study.).

3.3.1 Materials and methods

Participants

Twenty healthy students (13 males and 7 females), aged 20 to 31 years, volunteered to participate in the study. Inclusion criteria was no previous experience with perceptual studies. Demographic data are presented in Table 3.1. This sample size was chosen because no reference study was available which allowed for calculating optimal sample size.

[1]F = full vision condition; I = incomplete vision condition; R = visible Robot; C = visible club; H = visible club head; B = visible ball

Table 3.1: Demographic data of the participants (Mean±SD).

	n	Age [yr]	Height [cm]	Body mass [kg]	Handedness [left | right]
Female	7	24.5±3.5	169.0±4.9	61.4±3.6	1 | 6
Male	13	24.4±2.4	180.1±4.4	77.2±8.0	1 | 12
Total	20	24.5±2.7	176.2±7.2	71.7±10.2	2 | 18

All participants documented their experience (years of exercising and volume in hours per week) in four different groups of activities:

1. golf, field field hockey, and similar;
2. returning games, e.g. tennis and volleyball;
3. ball games, e.g. soccer and basketball;
4. computer games.

Table 3.2 and 3.3 shows the information provided by participants regarding their previous experience. This study was conducted in accordance with the declaration of Helsinki in its latest version. All participants provided written informed consent before participation. The study received a positive vote by the Ethical Committee of Technische Universität Darmstadt (TU Darmstadt).

Table 3.2: Experience in golf, field hockey, and similar sports and returning games (Mean±SD).

	Golf, field hockey and similar			Returning games		
	n	years	h/wk	n	years	h/wk
Female	0	–	–	2	13.5±12.0	7.7±10.2
Male	8[a]	2.1±1.7	2.2±2.6	9	5.2±7.5	2.1±1.5
Total	8	2.1±1.7	2.2±2.6	11	6.7±8.4	3.1±4.2

Means±SD were only calculated for participants reporting experience. [a] Experience in Golf, field hockey and similar sports was reported by a total of 10 participants, duration and volume were only reportet by 8 participants.

Table 3.3: Experience in ball games and computer games (Mean±SD).

	Ball games			Computer games		
	n	years	h/wk	n	years	h/wk
Female	2	8.5±2.1	7.0±4.2	2	3.2±2.0	0.5±0.5
Male	12	13.6±8.1	4.1±2.5	11	9.0±5.1	4.0±3.7
Total	14	12.8±7.4	4.2±2.9	13	8.5±4.7	2.4±3.3

Means±SD were only calculated for participants reporting experience.

Apparatus and task

BioRob System. The BioRob robot arm was used as a technical platform for the studies (see Fig 3.1). This system has four elastically actuated joints. Each joint is connected via four elastic springs with a separate actuator for each joint. The BioRob system was developed specifically for the physical interaction with humans. Due to its lightweight construction, the system generates low kinetic energy. The system is safe to use without collision detection. In order to adapt the system to the anthropometric properties of participants, the BioRob arm was attached to a special lightweight frame. This allows easy adjustment of the height and orientation of the robot arm (Kollegger, Ewerton, Wiemeyer, and Peters, 2018).

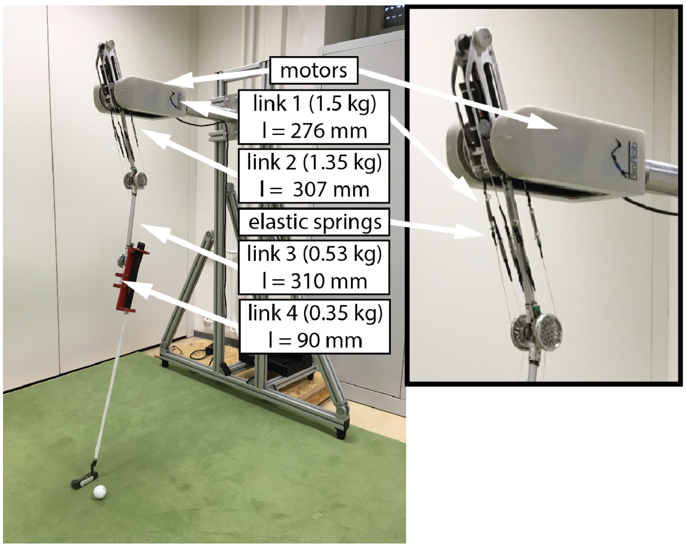

Figure 3.1: BioRob-System. BioRob with 4 DoF on a movable lightweight frame construction for experiments.

Artificial Putting Green. In order to enable a reproducible robot putt and a uniform rolling behavior of the golf balls, an artificial putting green was constructed (see Fig 3.2). The platform is six meters long and two meters wide. The surface consists of a short-pile carpet (Kollegger et al., 2018).

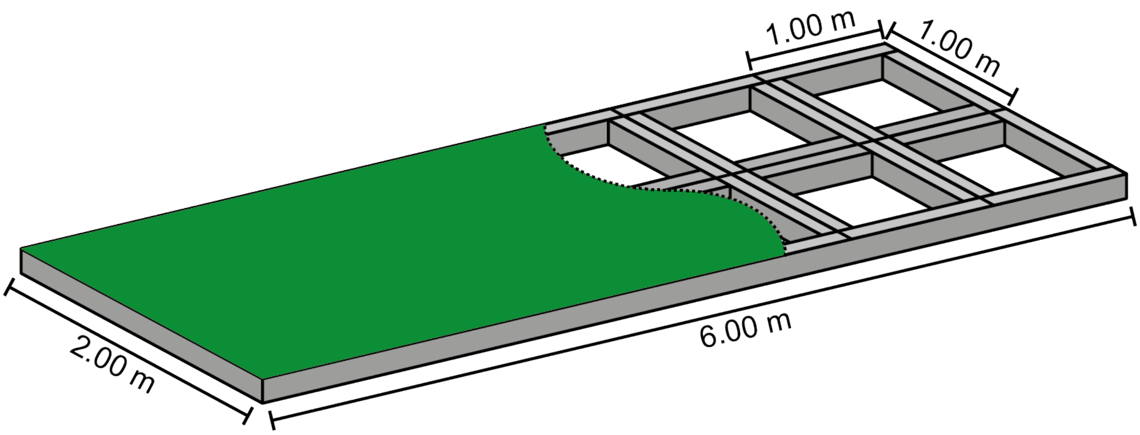

Figure 3.2: Artificial putting green. Schematic representation of the artificial putting green with substructure of aluminum profiles.

Video material. The robot performed putting movements over 6 different putting distances (1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m) on an artificial putting green. The robot motions were recorded using a Camcorder (Sony FDRAX33) with 50 frames per second. The camera was positioned at a distance of 2.6 m from the ball, perpendicular to the putting direction. A black mollitan was used as a background, which also covered the mounting frame of the BioRob system (see Fig 3.3).

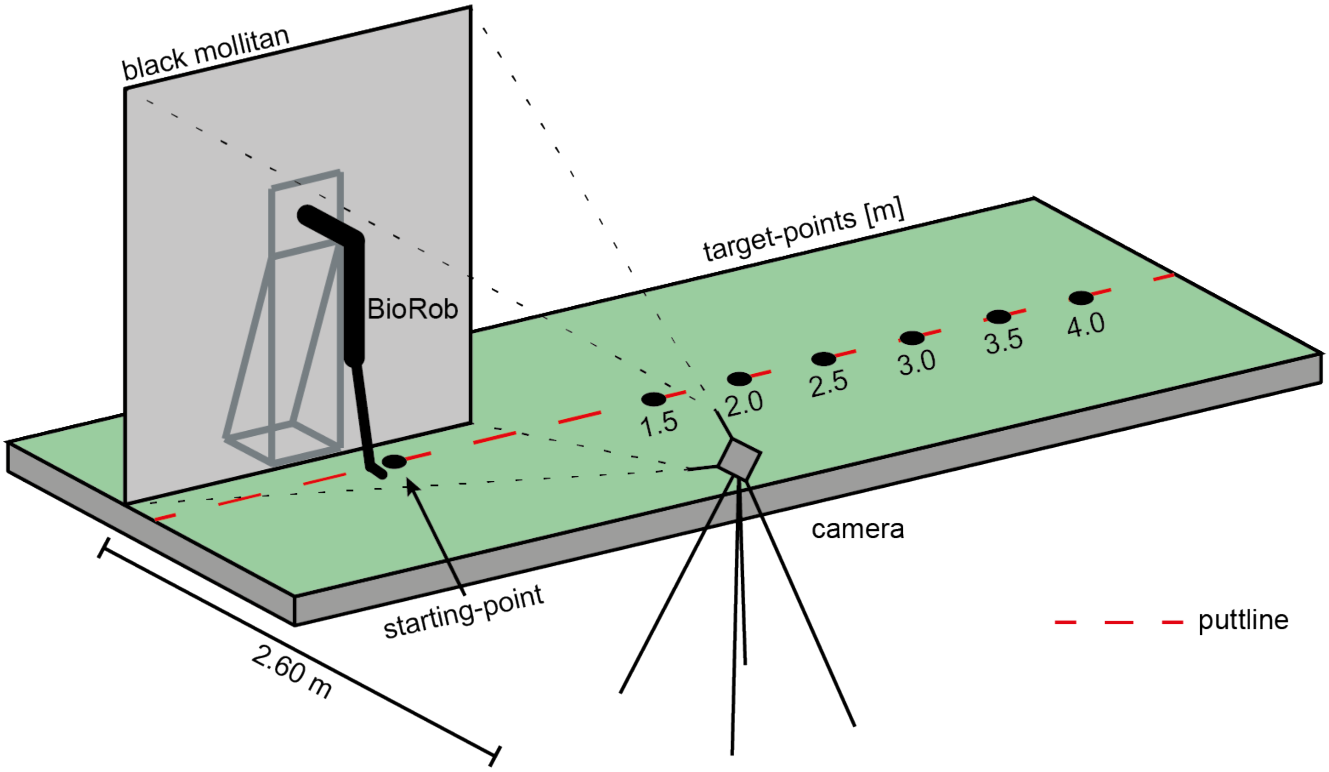

Figure 3.3: Video recording setup. Schematic representation of technical arrangement for the recording of the video material.

The presented video material was produced with Adobe Creative Cloud Premiere Pro CC 2018 (Version 12.0.0). All 12 video scenes had the same basic structure (see Fig 3.4 and Fig 3.5):

1. Preliminary phase: black screen (duration 3 s) with short beeps (duration 0.05 s) after 1 and 2 s, followed by a 1 s freeze frame of the robot in the starting position with a fixation cross centered on the handle and a 1 s beep;
2. Backswing phase: identical motion sequence from starting position to reversal point (duration 0.52 s). Regardless of the putting distance, velocity, joint angle, and reversal point were kept constant to avoid spatial cues in this phase;
3. Downswing phase: acceleration profiles from reversal to impact depending on putting distance;
4. Follow-through phase: rolling ball and club motion from impact until the ball passes the right boundary of the image.
   Note: The follow-through phase was presented only in the full vision condition.

Potential cues. The duration of the different phases and the total duration of the video for the different putting distances are illustrated in Table 3.4 and 3.5. In addition, the velocities of the club and the ball at

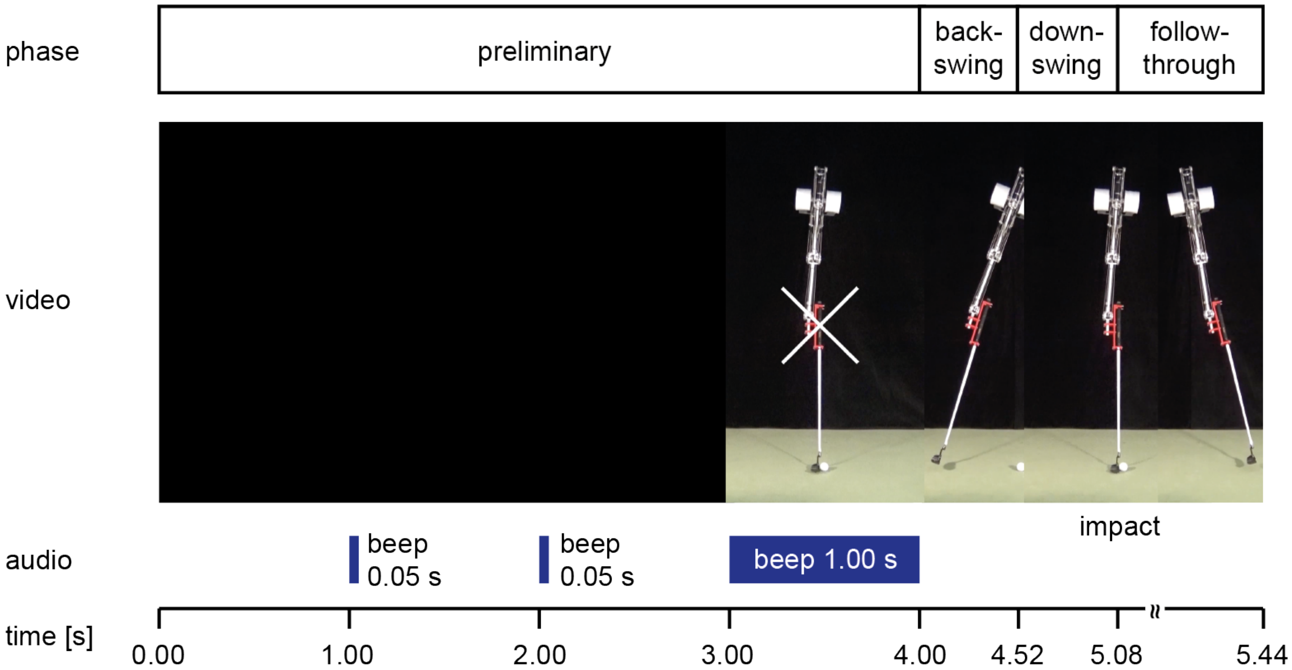

Figure 3.4: Video sequence in the full vision condition. Sequential presentation of a 2.0 m putt video in full vision condition with information about swing phase, audio signals and timing (video sequence see S1 Video).

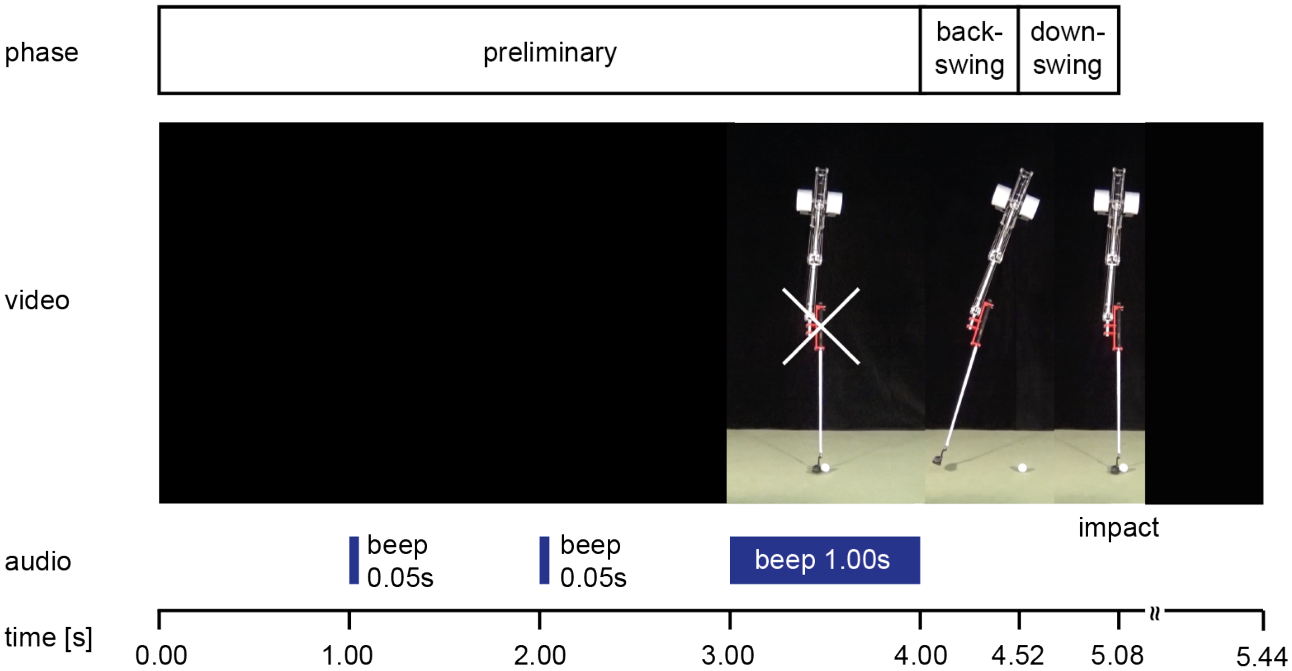

Figure 3.5: Video sequence in the incomplete vision condition. Sequential presentation of a 2.0 m putt video in incomplete vision condition with information about swing phase, audio signals and timing (video sequence see S2 Video).

the time of the impact are specified. The total duration of the preliminary ($t_{\text{preliminary phase}}$) and backswing ($t_{\text{backswing}}$) phases is the same (4 s) for all video sequences. The duration of the complete video sequences is reduced by 0.34 s from 5.54 s for a putting distance of 1.5 m to 5.20 s for a putting distance of 4.0 m. As the putting distance increases, the total duration of the downswing and follow-through phase decreases by 0.34 s from 1.02 s (downswing: 0.58 s; follow-through: 0.44 s) to 0.68 s (downswing: 0.46 s; follow-through: 0.22 s).

Table 3.4: Temporal and kinematic differences between the 6 putting distances under full and incomplete vision conditions.

	Full and incomplete vision condition			
Distance [m]	$t_{\text{Total-I-RCHB}}$ [s]	$t_{\text{preliminary phase}}$ [s]	$t_{\text{backswing}}$ [s]	$t_{\text{downswing}}$ [s]
1.5	5.10	4.00	0.52	0.58
2.0	5.08	4.00	0.52	0.56
2.5	5.06	4.00	0.52	0.54
3.0	5.04	4.00	0.52	0.52
3.5	5.02	4.00	0.52	0.50
4.0	4.98	4.00	0.52	0.46

$t_{\text{Total-I-RCHB}}$ = total duration of the video in the incomplete vision condition; $t_{\text{preliminary phase}}$ = duration of the preliminary phase; $t_{\text{backswing}}$ = duration of the backswing phase; $t_{\text{downswing}}$ = duration of the downswing phase.

Table 3.5: Temporal and kinematic differences between the 6 putting distances under full and incomplete vision conditions.

	Full vision condition			
Distance [m]	$v_{\text{C-impact}}$ [m/s]	$t_{\text{Total-F-RCHB}}$ [s]	$t_{\text{follow-through}}$ [s]	$v_{\text{B-Impact}}$ [m/s]
0.8	1.5	5.54	0.44	1.4
0.9	2.0	5.44	0.36	1.6
1.0	2.5	5.38	0.32	1.9
1.2	3.0	5.32	0.28	2.0
1.5	3.5	5.26	0.24	2.3
1.7	4.0	5.20	0.22	2.5

$v_{\text{C-impact}}$ = resulting velocity of the club head at the impact; $t_{\text{Total-F-RCHB}}$ = total duration of the video in the full vision condition; $t_{\text{follow-through}}$ = duration of follow-through phase; $v_{\text{B-Impact}}$ = resulting velocity of the ball after the impact.

The velocity of the club head at impact and the ball velocity immediately after impact increase with increasing putting distances. In the incomplete vision condition, there is restricted information depending on the different putting distances, these are the duration of the downswing phase ($t_{\text{downswing}}$), the total duration of the video ($t_{\text{Total-I-RCHB}}$) and the resulting velocity of the club head before the impact ($v_{\text{C-impact}}$). Additional spatio-temporal information is available in the full vision condition, i.e., the velocity of the ball after impact ($v_{\text{B-impact}}$), duration of follow-through phase ($t_{\text{follow-through}}$), and total duration ($t_{\text{Total-F-RCHB}}$), see Fig. 3.6. Furthermore, three spatial cues are delivered (see Table 3.6):

1. The distance covered by the ball and the club head in the x-direction after impact, as illustrated in Fig 3.7 (left) for the putting distances of 1.5 m and 4.0 m. In both cases, similar ball-to-club head relationships exist.
2. The distance of the club in the y-direction after impact. The covered distance of the club head varies depending on the putting distance between 3.0 cm and 5.3 cm (see Fig 3.7 center).
3. The radial distance between ball and club head after impact (see Fig 3.7 right).

Fig 3.7 shows a schematic representation of these additional cues.

Table 3.6: Comparison of available spatio-temporal information under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Phase	Information	F-RCHB	I-RCHB
Downswing	$t_{\text{downswing}}$	X	X
	t_{Total}	X	X
	$x_{\text{club downswing}}$	X	X
	$y_{\text{club downswing}}$	X	X
	$v_{\text{C-impact}}$	X	X
Follow-through	$v_{\text{B-impact}}$	X	
	$t_{\text{follow-through}}$	X	
	$x_{\text{club follow-through}}$	X	
	$y_{\text{club follow-through}}$	X	
	$x_{\text{ball follow-through}}$	X	
	rd	X	

$t_{\text{downswing}}$ = duration of the downswing phase; t_{Total} = total duration of the video; $x_{\text{club downswing}}$ = distance covered by the club head in x-direction in the downswing phase; $y_{\text{club downswing}}$ = distance covered by the club head in y-direction in the downswing phase; $v_{\text{C-impact}}$ = resulting velocity of the club head before the impact; $v_{\text{B-Impact}}$ = resulting velocity of the ball after the impact; $t_{\text{follow-through}}$ = duration of follow-through phase; $x_{\text{club follow-through}}$ = distance covered by the club head in x-direction in the follow-through phase; $y_{\text{club follow-through}}$ = distance covered by the club head in y-direction in the follow-through phase; $x_{\text{ball follow-through}}$ = distance covered by the ball in x-direction in the follow-through phase; rd = radial distance between club head and ball in the follow-through phase.

Experimental setup. The video sequences were presented by a self-developed computer program. Video clips were displayed by a projector (EPSON EB-1860, resolution: 1024 x 768 px) in original size at the end of the artificial putting green. The BioRob system was projected in its real size, i.e., 1.42 m. Participants watched the video sequences from a distance of 3.0 m while sitting at a table (see Fig 3.8).

Each of the 12 video sequences was shown four times to the participants in randomized order (total of 48 clips). Upon completion of each sequence, a visual analog scale (0.0 to 6.0 m) was presented to the participants by the computer program. The scale was displayed with a width of 1.050 px (spatial resolution: 0.57 cm/px). Participants documented their length prediction by clicking at the respective point on the scale with the mouse cursor.

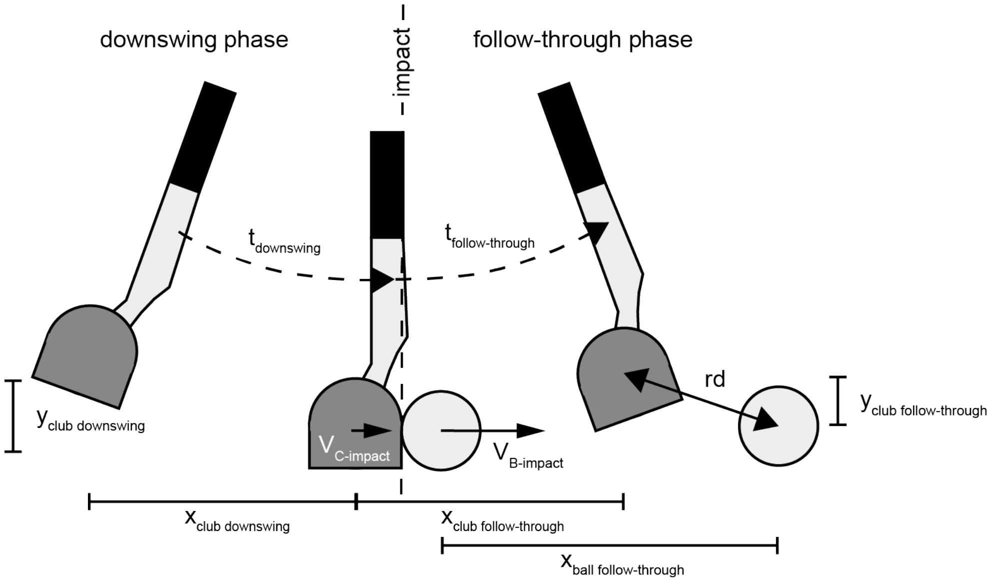

Figure 3.6: Potential cues. Schematic representation of $t_{downswing}$ = duration of the downswing phase; $v_{C\text{-}impact}$ = resulting velocity of the club head before the impact; $x_{club\ downswing}$ = distance covered by the club head in x-direction in the downswing phase; $y_{club\ downswing}$ = distance covered by the club head in y-direction in the downswing phase; $v_{B\text{-}Impact}$ = resulting velocity of the ball after the impact; $t_{follow\text{-}through}$ = duration of follow-through phase; $x_{club\ follow\text{-}through}$ = distance covered by the club head in x-direction in the follow-through phase; $y_{club\ follow\text{-}through}$ = distance covered by the club head in y-direction in the follow-through phase; $x_{ball\ follow\text{-}through}$ = distance covered by the ball in x-direction in the follow-through phase; rd = radial distance between club head and ball.

Following the estimation of the putting distance, participants documented the confidence of their decision on a five-point scale (very unsure, unsure, undecided, sure, and very sure). In addition to the prediction of the putting distance and the confidence, the response time, i.e. time elapsed between the end of the video presentation and the final click on the distance scale, was also recorded. After assessment, the next video was started by clicking a button. All data was stored by the computer program in one file for each participant.

Procedure. First, the participants were introduced to the laboratory and the experimental setup by the experimenter. After this introduction, all participants received an informed consent document and a participant questionnaire. After signing the consent and completing the questionnaire, the test software was presented to the participants and the experimental procedure was described (Fig 3.8). The participants read the instructions and any questions were answered by the experimenter. After the introductory phase, the participants started the experiment autonomously according to the procedure explained in the previous section. After completion of the test program, the participants were debriefed.

Data processing and analysis. Based on the predicted putting distance, absolute error (AE), constant error (CE) and the variable error (VE) were calculated (Schmidt, Lee, Winstein, Wulf, and Zelaznik, 2018, p.23-56). A two-way ANOVA with repeated measures was calculated with the two factors of putting distance (6 distances) and vision condition (full versus incomplete). Wilcoxon tests were applied for

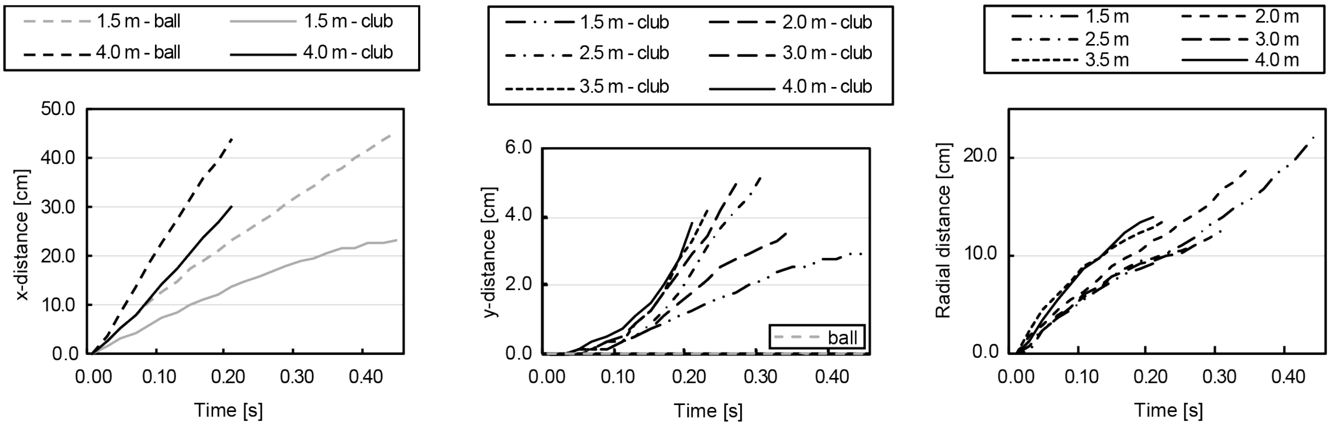

Figure 3.7: Schematic representation of potential cues in the follow-through phase. **Left:** Covered distance of ball and racket in x-direction after impact for putting distances 1.5 m and 4.0 m. **Center:** Covered distance of ball and racket in y-direction after impact for all putting distances. **Right:** Schematic representation of radial distance (rd) between club and ball. Note: Plots show real values measured with actual robot movements which were not perfectly smooth.

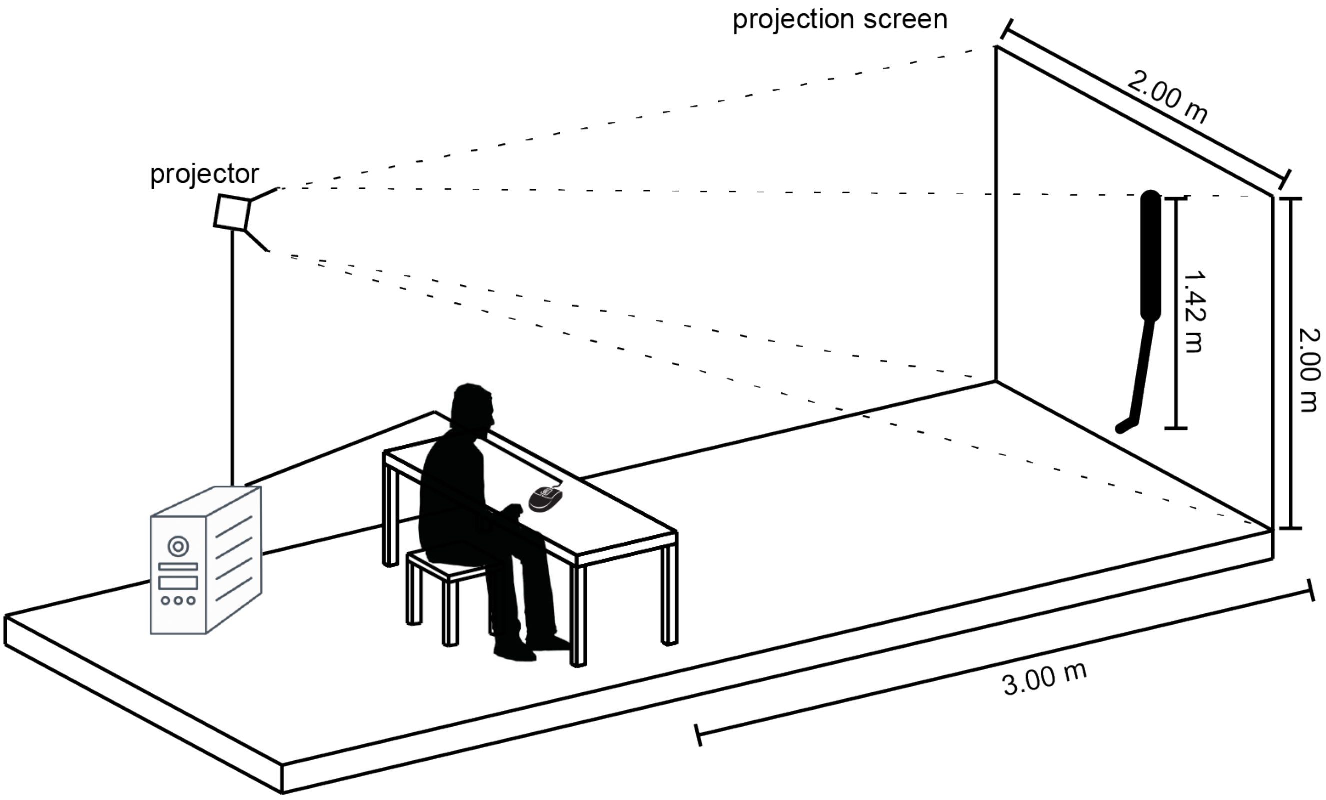

Figure 3.8: Experimental setup. Schematic representation of the experimental setup with the projection screen and the position of the participant.

follow-up analysis. Bonferroni corrections were applied to multiple comparisons. All statistical analyses were calculated using SPSS 24 (SPSS Inc., Chicago, USA). Level of significance was set a priori to 0.05.

3.3.2 Results

The following section describes the results of the study 1. A dataset with the raw data and the calculated values can be found in the supporting information (see S1 Dataset).

Prediction of the putting distance

Figure 3.9 and Table 3.7 show the means and standard deviations of the predicted putting distance for the six real putting distances under the two experimental conditions. The prediction of the putting distance differs under the two conditions with the exception of the putting distance of 2.0 m. Under the full vision condition, all distances are overestimated and the estimated putting distance increases with increasing distance of the putts presented to the participants. The distance prediction under the incomplete vision condition does not correspond to the real distance; estimations show a slight increase (by 0.54 m) in the range of the real putting distance from 1.5 to 2.5 m. In the distance range from 2.5 to 4 m, the prediction remains constant (3.15 to 3.05 m). Shorter distances (1.5 - 3.0 m) are overestimated, while longer distances (3.5 - 4.0 m) are underestimated.

Table 3.7: Predicted distance under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Predicted distance [m]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	2.61±0.95	2.88±1.11	3.15±1.06	3.15±1.21	3.07±1.06	3.05±0.99
F-RCHB	2.47±1.05	2.89±0.94	3.66±0.99	3.83±1.11	4.36±1.02	4.62±1.00

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision conditions: full and incomplete vision) revealed significant main effects of vision condition and distance as well as a significant interaction effect (see Table 3.8).

Table 3.8: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the predicted putting distance. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19.00	35.86	<.001	.654
Distance	2.35	44.64	50.47	<.001	.726
Vision condition x distance	3.78	71.85	42.90	<.001	.693

A follow-up analysis using a Wilcoxon test with Bonferroni correction (see Table 3.9) revealed significant differences between the vision conditions at all distances, except for the short putting distances of 1.5 and 2.0 m.

Constant error (CE)

The constant error indicates the accuracy of the prediction of the putting distance with respect to the actual length of the putt, i.e., the average error. Under the incomplete vision condition the constant error

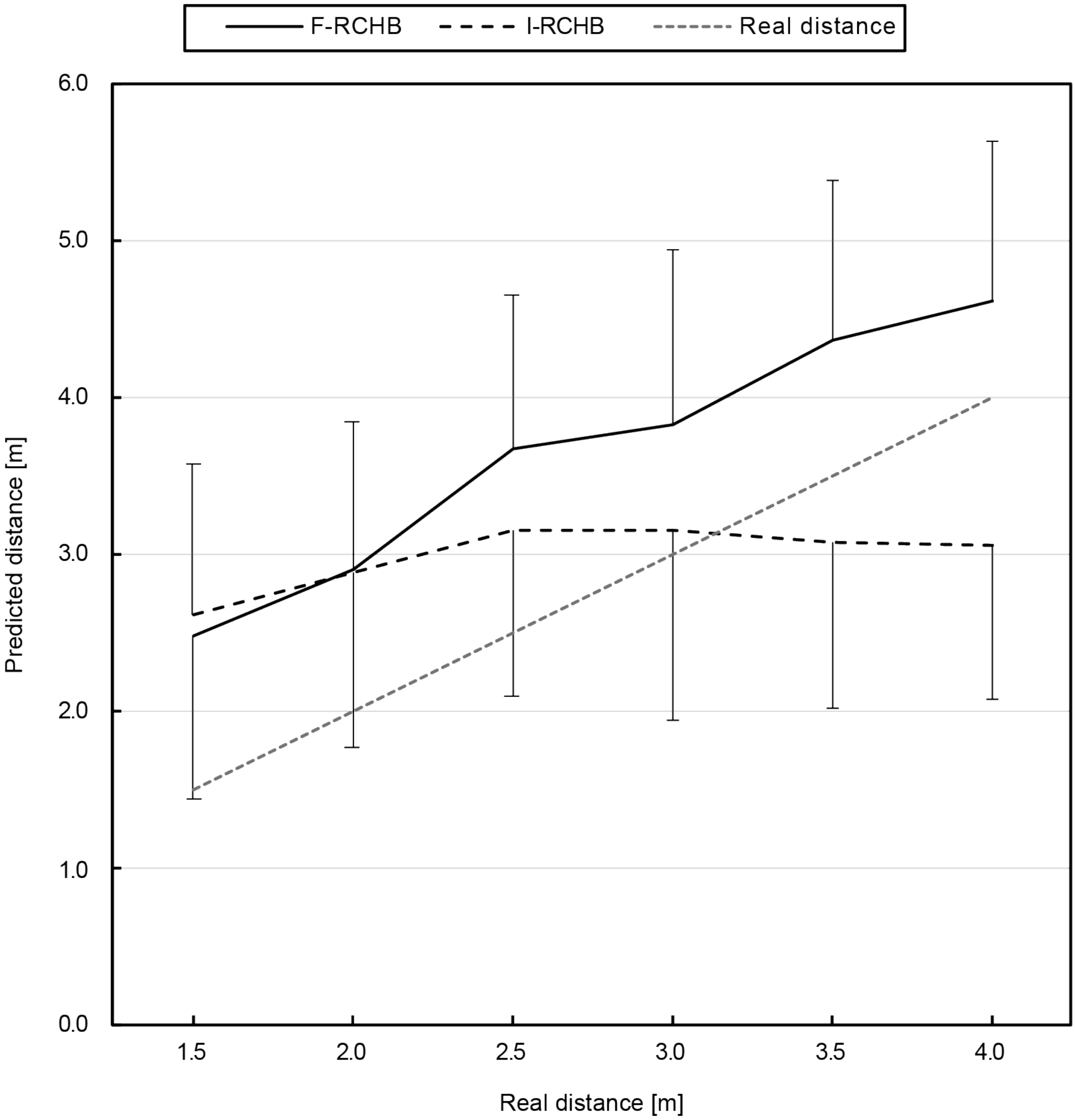

Figure 3.9: Predicted putting distance. Mean and standard deviation of the predicted putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

decreases from 1.11 m (2.5 m) to 0.15 m (3.0 m) with increasing distances for small and medium distances. For longer distances, the sign changes and the constant error increases to -0.95 m (4.0 m). In contrast, the constant error under the constant vision condition is fairly constant (within a range of 0.62 to 1.16 m), showing a slightly decreasing trend with increasing putting distance (see Fig 3.10 and Table 3.10).

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision

Table 3.9: Follow-up analyses (Wilcoxon test with Bonferroni correction) of the interaction of putting distance and vision condition for predicted putting distance.

	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
N	20	20	20	20	20	20
Z	-1.755	-.485	-3.099	-3.192	-3.920	-3.920
2p	.079	.627	.002*	.001*	<.001*	<.001*

* Significant after Bonferroni correction. Level of significance $p < .008\overline{3}$

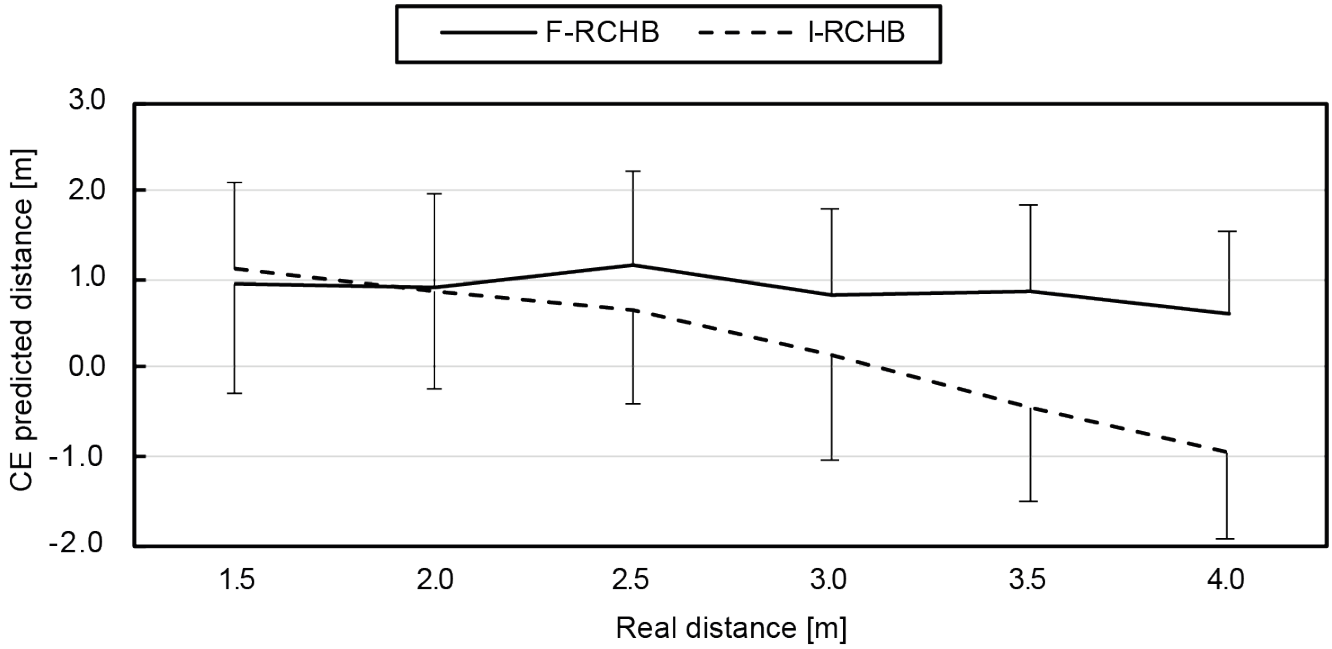

Figure 3.10: Constant error. Mean and standard deviation of the constant error of predicted putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Table 3.10: Constant error of predicted distance under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Constant error of predicted distance [m]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	1.11±0.95	0.88±1.11	0.65±1.06	0.15±1.21	-0.43±1.06	-0.95±0.99
F-RCHB	0.97±1.05	0.89±0.94	1.16±0.99	0.83±1.11	0.86±1.02	0.62±1.00

conditions: full and incomplete vision) revealed significant main effects of vision condition and distance as well as a significant interaction effect (see Table 3.11).

A follow-up analysis using a Wilcoxon test with Bonferroni correction (see Table 3.12) revealed significant differences between the vision conditions at all distances, except for short putting distance of 1.5 and 2.0 m.

Table 3.11: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the constant error of the predicted putting distance. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19.00	35.86	<.001	.654
Distance	2.35	44.64	45.49	<.001	.705
Vision condition x distance	3.78	71.85	42.90	<.001	.693

Table 3.12: Follow-up analyses (Wilcoxon test with Bonferroni correction) of the interaction of putting distance and vision condition for constant error.

	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
N	20	20	20	20	20	20
Z	-1.755	-.485	-3.099	-3.192	-3.920	-3.920
2p	.079	.627	.002*	.001*	<.001*	<.001*

* Significant after Bonferroni correction. Level of significance $p < .008\overline{3}$

Variable Error (VE)

Variable error indicates the consistency of the estimate of the putting distance, i.e., the variability of the participants around the mean of prediction of the putting distance. As can be seen in Fig 3.11 and Table 3.13, variable error is rather constant under the full vision condition, whereas it slightly increases with increasing putting distance under the incomplete vision condition.

Table 3.13: Variabl error of predicted distance under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Variable error of predicted distance [m]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	0.58±0.32	0.64±0.41	0.58±0.41	0.72±0.41	0.64±0.46	0.65±0.35
F-RCHB	0.65±0.52	0.63±0.36	0.59±0.27	0.63±0.34	0.57±0.31	0.51±0.30

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision conditions: full and incomplete vision) revealed no significant main effects of vision condition and distance or interaction effect (see Table 3.14).

Absolute Error (AE)

The absolute error measure is the absolute average between the prediction and the real distance. Under the incomplete vision condition, the absolute error initially decreases with increasing real putting distance and increases again at 4.0 m. Under the complete vision condition, the absolute error decreases from the

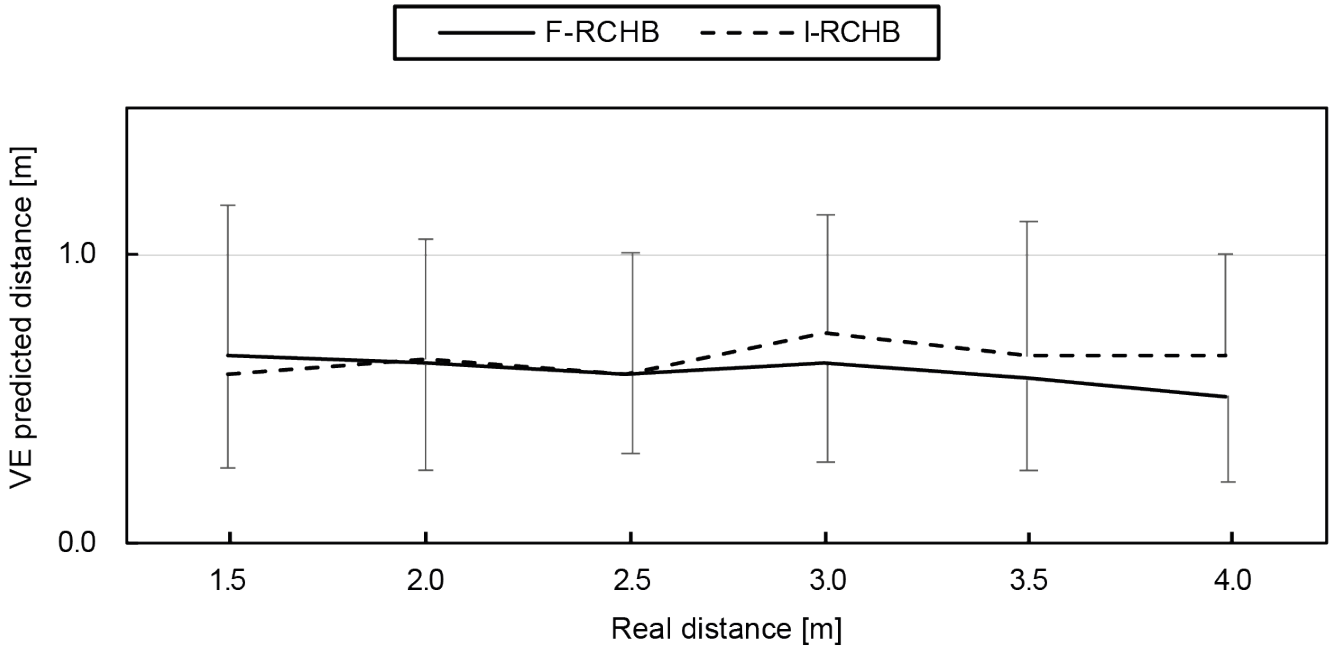

Figure 3.11: Variable error. Mean and standard deviation of the variable error of predicted putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Table 3.14: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the variable error of the predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19.00	1.09	.310	
Distance	3.56	67.70	.454	.748	
Vision condition x distance	3.78	71.74	.808	.581	

real putting distance of 1.5 to 2.0 m, increases at a putting distance of 3.0 m and then decreases to its minimum at 4.0m (Fig 3.12 and Table 3.15).

Table 3.15: Absolute error of predicted distance under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Absolute error of predicted distance [m]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	1.21±0.81	1.12±0.87	0.99±0.75	0.99±0.69	0.91±0.69	1.14±0.75
F-RCHB	1.08±0.92	1.00±0.82	1.27±0.85	1.12±0.80	1.11±0.73	0.99±0.63

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision conditions: full and incomplete vision) revealed no significant main or interaction effects (see Table 3.16).

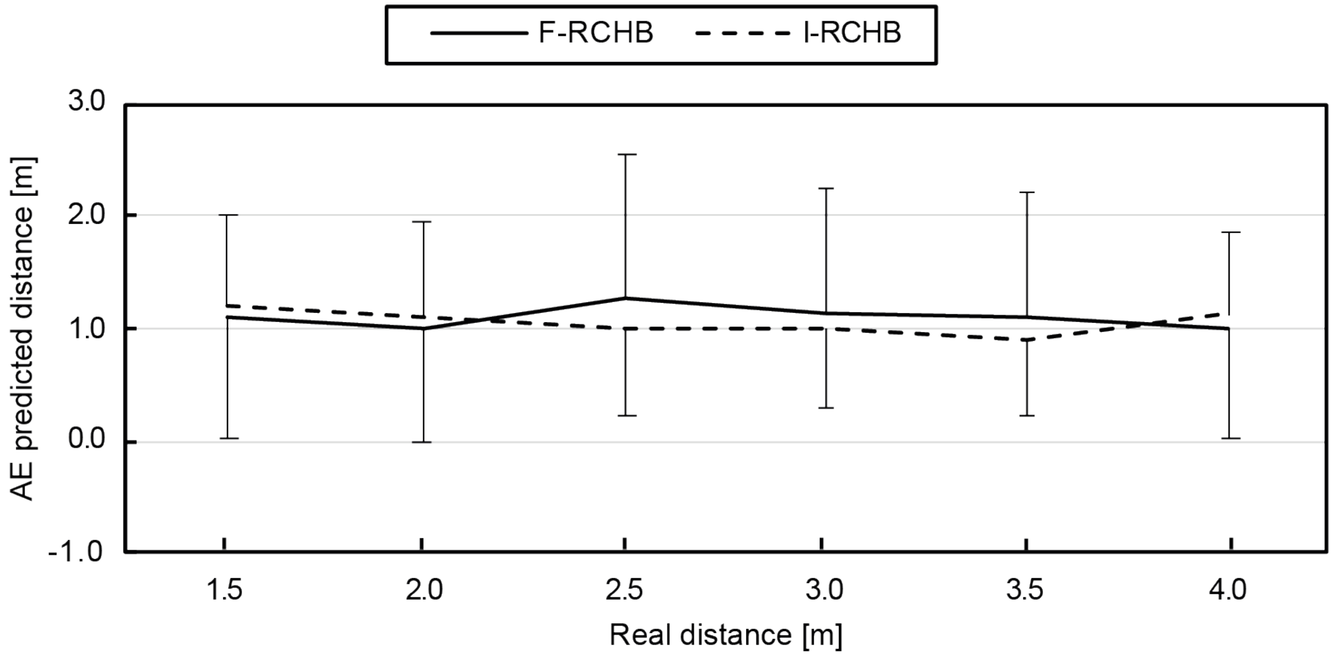

Figure 3.12: Absolute error. Mean and standard deviation of the absolute error of predicted putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Table 3.16: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the absolute error of the predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19.00	.174	.681	
Distance	2.30	43.78	.356	.732	
Vision condition x distance	2.50	47.45	2.05	.129	

Confidence of prediction

Confidence was recorded on a five-point scale with the values: (1) very unsure, (2) unsure, (3) undecided, (4) sure, and (5) very sure. Fig 3.13 and Table 3.17 show the means and standard deviations of the confidence of the predicted putting distance of all participants for the six real putting distances under the two experimental conditions. The confidence of the predicted putting distance differs under the two conditions over all distances. Under the complete vision condition, confidence of prediction was higher at all distances and shows a slight increase with increasing putting distance from 3.09 at 2.0 m to 3.40 at 4.0 m. Under the incomplete vision condition, the confidence reaches the highest value at the putting distance of 1.5 m (2.70), remains nearly constant and decreases at the putting distance of 4.0 m to the lowest value of 2.57.

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision conditions: full and incomplete vision) revealed a significant main effect of vision condition (see Table 3.18).

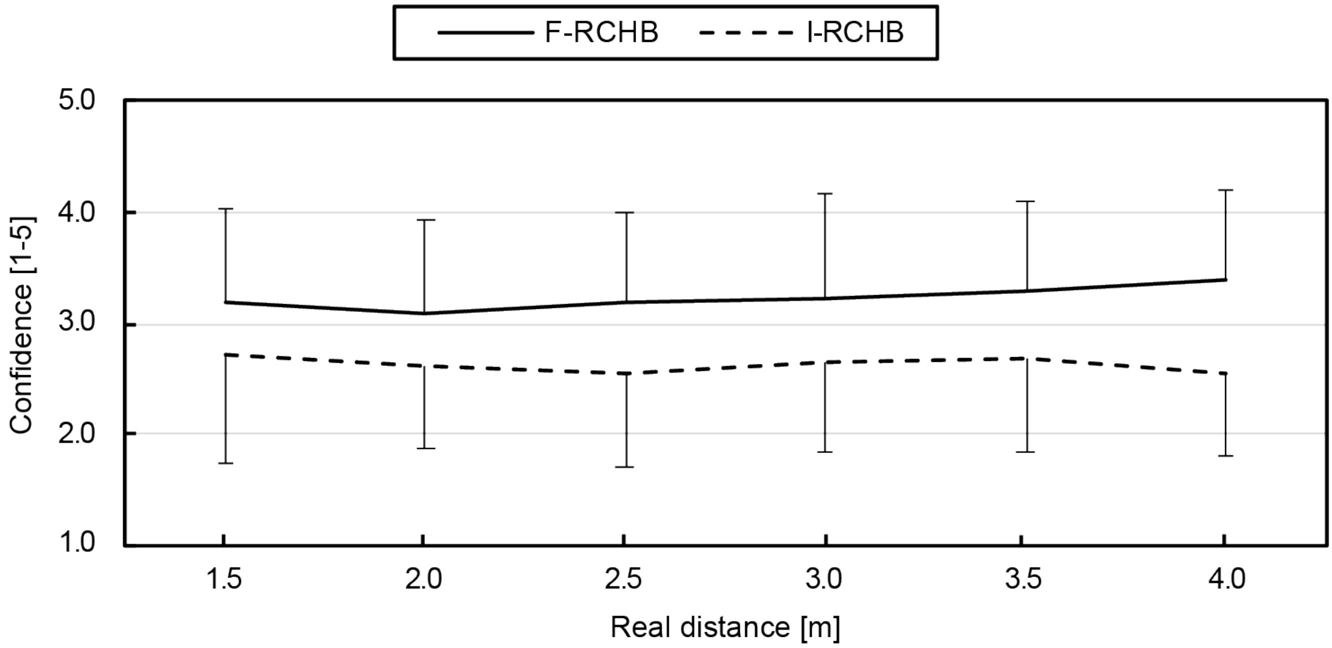

Figure 3.13: Confidence of prediction. Mean and standard deviation of the confidence of prediction depending on the real putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Table 3.17: Confidene of prediction under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Confidence [1-5]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	2.70±0.85	2.63±0.83	2.56±0.84	2.66±0.94	2.68±0.83	2.57±0.80
F-RCHB	3.19±0.84	3.09±0.81	3.18±0.76	3.24±0.77	3.27±0.81	3.40±0.72
Difference	0.49	0.46	0.62	0.58	0.60	0.85

Table 3.18: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the confidence of the prediction. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19.00	41.34	<.001	.685
Distance	3.34	63.41	1.46	.232	.071
Vision condition x distance	3.56	67.66	2.10	.098	.100

Response time

The response time was measured as the time between the end of the video sequence and the final mouse click on the meter scale. Fig 3.14 and Table 3.19 show the means and standard deviations of the response time of all participants for the six real putting distances under the two experimental conditions. The response time in the two conditions differs over all distances and is lower under the complete vision condition. With increasing distance, the response time under the complete vision condition at shorter distances decreases from 4.64 s (1.5 m) to 4.17 s (2.5 m) followed by an increase to 5.13 s (3.0 m). For longer distances, the response time decreases again as the distance increases, reaching its minimum at 3.38 s (4.0 m). Under the incomplete vision condition, the response time decreases from 5.70 s (1.5 m) to 4.47 s (2.0 m) and increases to 5.61 and 5.77 s for medium distances (2.5 and 3.0 m). For long distances, the response time decreases from the medium distances to 4.99 s (3.5 m) and 5.33 s (4.0 m).

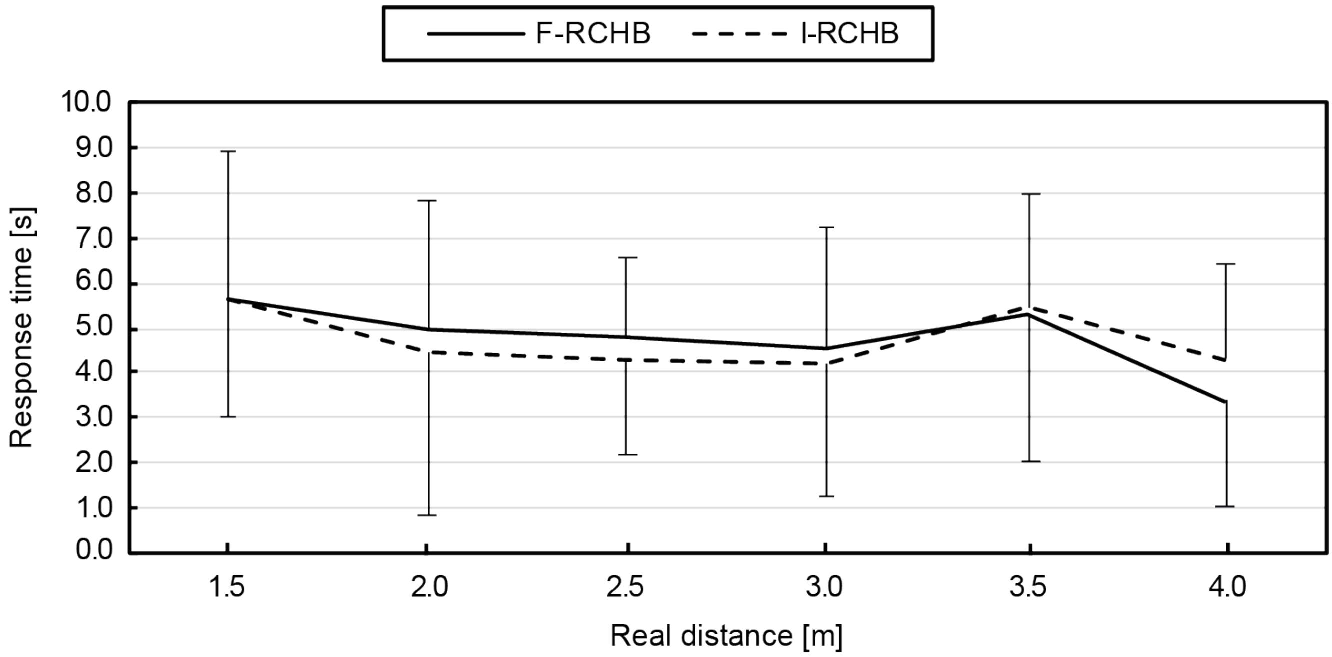

Figure 3.14: Response time. Mean and standard deviation of the response time depending on the real putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition.

Table 3.19: Response time depending on the real putting distance under full (F-RCHB) and incomplete (I-RCHB) vision condition (Mean±SD).

	Response time [s]					
Condition	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
I-RCHB	5.70±5.87	4.47±2.97	5.61±5.80	5.77±4.55	4.99±4.25	5.33±4.56
F-RCHB	4.64±4.54	4.35±4.33	4.17±4.29	5.13±6.37	4.61±5.57	3.38±3.40

The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 m; 2 vision conditions: full and incomplete vision) revealed a significant main effect of vision condition (see Table 3.20).

3.3.3 Discussion

In this section, the results of Study 1 are briefly discussed to provide a transition to Study 2. A complete discussion of the results of Study 1 and 2 will be included in the overall discussion. The results show that participants were able to predict the putting distance of a robot putt under the complete vision condition. However, all six putting distances were overestimated by the participants, a linear course of the predicted

Table 3.20: Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the response time. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.00	19	50.17	<.001	.725
Distance	3.60	68.39	2.54	.053	.118
Vision condition x distance	3.02	57.39	1.14	.342	.056

putting distances is shown with increasing real putting distance. This systematic overestimation supports the predictions derived from the FLE. However, contrary to hypothesis 1, prediction error (CE) does not increase, but rather decreases with increasing putting distance. In contrast to the full vision condition, the participants could not predict the putting distance under the incomplete vision condition. The predicted values seem to be randomly chosen values that show a tendency to the centre of the prediction scale (0 to 6m) at 3.00 m. The confidence data support the prediction results, because the confidence of the decision was higher under full vision for all distances. The visibility of the follow-through-phase was found to have a decisive influence on the quality of the prediction of the putting distance. This leads to the conclusion that the additional cues available under the full vision condition have a high relevance for the prediction of putting movements. It remains open what influence individual elements (e.g. club and robot) have on the prediction of the putting distance. Whereas hypothesis 2 (different prediction depending on vision condition) was confirmed, there was no evidence for hypothesis 1 (increasing error with increasing putting distance). Ex post calculations of power using the software G*Power 3.1.9.4 Faul, Erdfelder, Lang, and Buchner, 2007 revealed that study 1 was over-powered (1.0) regarding hypothesis 2 (Protocol of power analysis see S1 File). Power analysis for hypothesis 1 does not make sense due to the decrease of error, which is contrary to hypothesis 1.

3.4 Study 2 – Prediction and visibility manipulation

This study is based on the results of study 1. In addition to a replication of the previous results (hypotheses 1 and 2), the influence of the visibility of the ball, club and robot after the impact on the prediction of the putting distance is investigated (spatial occlusion; hypothesis 3). In this study, video sequences of robot putts at three different distances are presented to the participants. For each distance, videos are shown under four different visual conditions, i.e. full vision condition (F-RCHB), incomplete vision condition (I-RCHB), full vision condition with visible robot, club and club head in the follow-through-phase (F-RCH), and full vision condition with visible ball in the follow-through-phase (F-B).

In the following, only differences in materials and methods compared to study 1 are presented.

3.4.1 Materials and methods

Participants

Nineteen healthy students (11 males and 8 females), aged 19 to 36 years, volunteered to participate in the study. Inclusion criteria was no previous experience with perceptual studies. Demographic data are presented in Table 3.21. Whereas the results from Study 1 resulted in an optimal sample size of 4 participants (hypothesis 2), estimated sample size for testing hypothesis 3 was 12 participants Faul et al., 2007(Protocol of power analysis see S2 File). Taking into account the "winner's curse phenomenon", it is expected that the true effect size of study 1 regarding hypothesis 2 will be smaller. Therefore, the replication study will test a similar number of participants (N = 19) as in Study 1 Button et al., 2013.

Table 3.21: Demographic data of the participants (Mean±SD).

	n	Age [yr]	Height [cm]	Body mass [kg]	Handedness [left | right]
Female	8	24.0±3.2	166.0±6.6	59.0±5.3	3 | 5
Male	11	26.0±4.8	182.0±5.5	83.0±8.7	0 | 12
Total	19	25.0±4.3	176.0±9.8	73.0±14.0	3 | 17

Table 3.22 and 3.23 shows the information provided by participants regarding their previous experience in four different groups of activities (see Study1 - Participants). This study also conducted in accordance with the declaration of Helsinki in its latest version. All participants provided written informed consent before participation. The study received a positive vote by the Ethical Committee of TU Darmstadt.

Table 3.22: Experience in golf, field hockey, and similar sports and returning games (Mean±SD).

	Golf, field hockey and similar			Returning games		
	n	years	h/wk	n	years	h/wk
Female	3	3.8±3.8	3.5±3.2	4	8.3±8.8	1.5±0.5
Male	5	4.9±3.4	8.4±7.8	7	9.0±5.8	3.9±3.0
Total	8	4.5±3.3	6.6±6.6	11	8.7±6.6	3.0±2.6

Means±SD were only calculated for participants reporting experience.

Table 3.23: Experience in ball games and computer games (Mean±SD).

	Ball games			Computer games		
	n	years	h/wk	n	years	h/wk
Female	5	5.2±4.2	4.6±3.0	5	11.0±6.5	3.0±1.4
Male	11	16.2±8.4	7.8±9.2	11	12.1±6.3	10.7±10.1
Total	16	12.8±8.9	6.8±7.9	16	11.8±6.2	7.7±9.3

Means±SD were only calculated for participants reporting experience.

Apparatus and task

Based on the video recordings produced for Study 1 (see Study1 - Apparatus and task), additional scenes for the conditions F-RCH (full vision – robot, club, and club head visible) and F-B (full vision - robot and ball) were created for the three distances (2.0, 3.0, and 4.0 m). All 12 video scenes have the same basic structure (see Fig 3.4, Fig 3.5):

1. Preliminary phase
2. Backswing phase
3. Downswing phase
4. Follow-through phase: rolling ball and club motion from impact until the ball passes the right boundary of the image (see Fig 3.4). Note: In the F-RCH/F-B only the club and robot/ball were presented. The follow-through-phase was not presented in the I-RCHB.

In addition to the video sequences of the distance of 2.0 m in conditions F-RCHB (S1 Video) and I-RCHB (S2 Video), the video sequences of conditions F-RCH (S3 Video) and F-B (S4 Video) are available as supporting information.

Potential cues. Since the same video sequences were used as in study 1, the possible cues are analogous to this study (see Table 3.24).

Table 3.24: Comparison of available spatio-temporal information in F-RCHB, I-RCHB, F-RCH, and F-B. Explanations: see text.

Phase	Information	F-RCHB	I-RCHB	F-RCH	F-B
Downswing	$t_{\text{downswing}}$	X	X	X	X
	t_{Total}	X	X	X	X
	$\text{x}_{\text{club downswing}}$	X	X	X	X
	$\text{y}_{\text{club downswing}}$	X	X	X	X
	$v_{\text{C-impact}}$	X	X	X	X
Follow-through	v_{Bimpact}	X			X
	$t_{\text{follow-through}}$	X		X	X
	$x_{\text{club follow-through}}$	X		X	
	$y_{\text{club follow-through}}$	X		X	
	$x_{\text{ball follow-through}}$	X			X
	rd	X			

$t_{\text{downswing}}$ = duration of the downswing phase; t_{Total} = total duration of the video; $x_{\text{club downswing}}$ = distance covered by the club head in x-direction in the downswing phase; $y_{\text{club downswing}}$ = distance covered by the club head in y-direction in the downswing phase; $v_{\text{C-impact}}$ = resulting velocity of the club head before the impact; $v_{\text{B-Impact}}$ = resulting velocity of the ball after the impact; $t_{\text{follow-through}}$ = duration of follow-through phase; $x_{\text{club follow-through}}$ = distance covered by the club head in x-direction in the follow-through phase; $y_{\text{club follow-through}}$ = distance covered by the club head in y-direction in the follow-through phase; $x_{\text{ball follow-through}}$ = distance covered by the ball in x-direction in the follow-through phase; rd = radial distance between club head and ball.

Experimental setup. The video sequences were presented in the same way as in study 1 (see Study1 - Apparatus and task).

Procedure. The same procedure as in study 1 was used (see Study 1 - Apparatus and task).

Data processing and analysis. Based on the predicted putting distance, constant error (CE), constant error (CE) and the variable error (VE) were calculated Schmidt et al., 2018, p.55-61. A two-way ANOVA with repeated measures was calculated with the two factors of putting distance (3 distances) and vision condition (F-RCHB, I-RCHB, F-RCH, and F-B). Wilcoxon tests were applied for follow-up analysis. Bonferroni corrections were applied to multiple comparisons. All statistical analyses were calculated using SPSS 24 (SPSS Inc., Chicago, USA). Level of significance was set a priori to 0.05.

3.4.2 Results

The following section describes the results of study 2. A dataset with the raw data and the calculated values can be found in the supporting information (see S2 Dataset).

Prediction of the putt length

Figure 3.15 and Table 3.25 show the means and standard deviations of the predicted putting distance of all participants for the three real putting distances under the four experimental conditions.
Under the F-RCHB, F-RCH, and F-B conditions, the predicted putting distance increases with increasing real putting distance. All distances are overestimated under the F-RCHB and F-RCH conditions. Under the F-B condition, the distances of 2.0 and 3.0 m are overestimated, whereas the distance of 4m is slightly underestimated. The predicted distances under the I-RCHB condition show a small increase from 2.81 m (distance 2.0 m) to 3.22 m (distance 4.0 m). The distance of 2.0 m is overestimated and the distances of 3.0 and 4.0 m are underestimated.

Table 3.25: Predicted distance under the I-RCHB, F-RCHB, F-RHC, and F-B conditions (Mean±SD).

	Predicted distance [m]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	2.82±1.12	2.93±1.15	3.22±1.07
F-RCHB	3.12±0.97	3.55±0.94	4.24±1.04
F-RCH	2.89±0.95	3.44±0.98	3.94±1.15
F-B	3.07±0.86	3.71±1.01	4.34±1.14

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0, and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) revealed significant main effects of vision condition and distance as well as a significant interaction effect for predicted putt length (see Table 3.26).

Table 3.26: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.92	34.50	12.04	<.001	.401
Distance	1.59	28.58	62.15	<.001	.775
Vision condition x distance	4.56	82.08	4.25	.002	.191

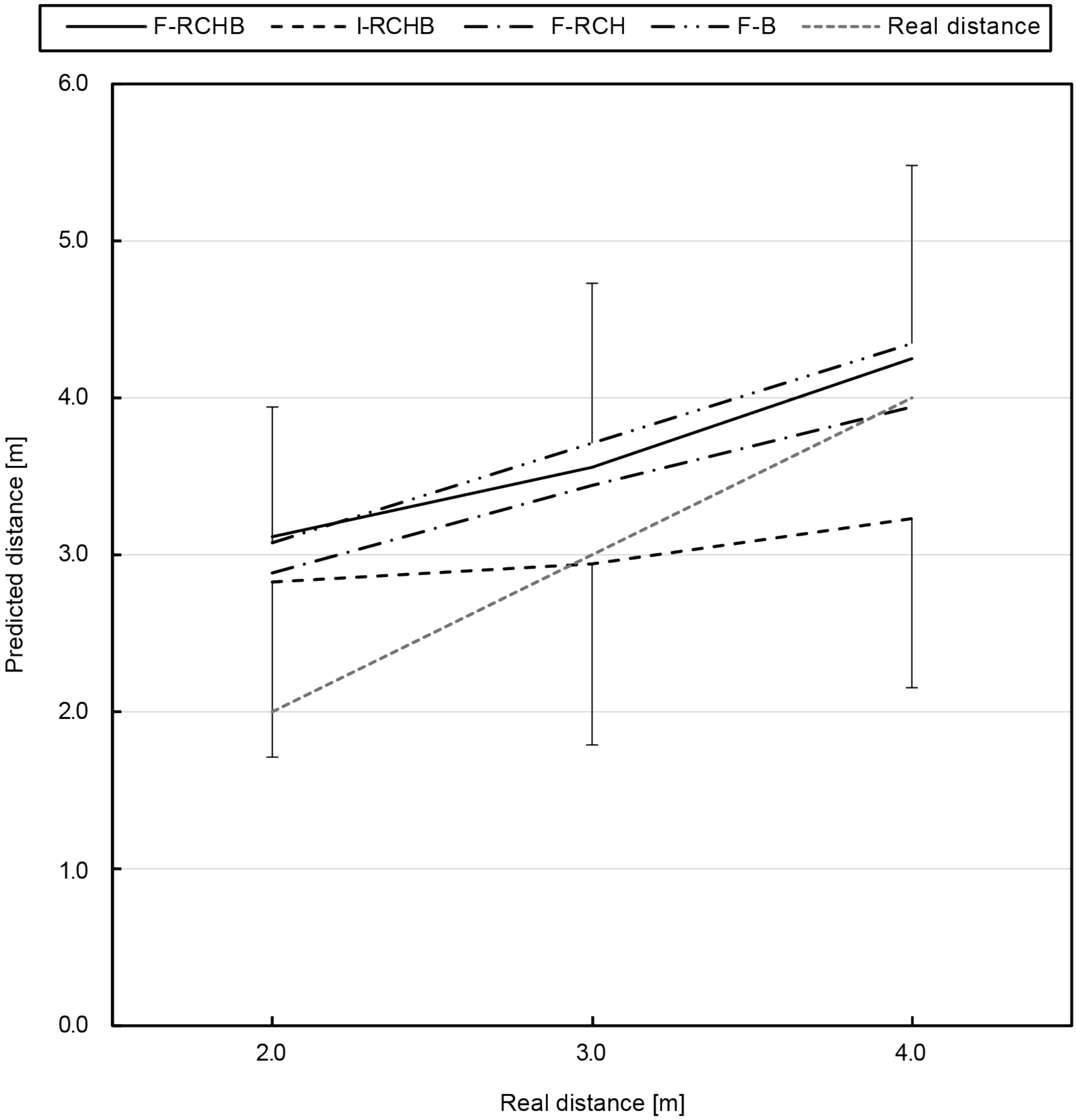

Figure 3.15: Predicted putting distance. Mean and standard deviation of the predicted putting distance under I-RCHB, F-RCHB, F-RCH, and F-B condition.

A follow-up analysis using a Wilcoxon test with Bonferroni correction (see Table 3.27) revealed no significant differences between the vision conditions at the real distance of 2.0 m. For the real distance of 3.0 m significant differences between the I-RCHB and the two manipulated vision conditions (F-RCH and F-B) are revealed. At a distance of 4.0 m there are significant differences between the incomplete (I-RCHB) and the three full (F-RCHB, F-RCH, and F-B) vision conditions.

Table 3.27: Follow-up analyses (Wilcoxon test and Bonferroni correction) of the interaction of putting distance and vision condition for predicted putt length at the real putting distance.

		I-RCHB vs. F-RCHB	I-RCHB vs. F-RCH	I-RCHB vs. F-B	F-RCHB vs. F-RCH	F-RCHB vs. F-B	F-HCB vs. F-B
	N	19	19	19	19	19	19
2.0 m	Z	1.650	-.322	-1.368	-1.408	-.724	-1.127
	2p	.099	.748	.171	.159	.469	.260
	N	19	19	19	19	19	19
3.0 m	Z	2.495	-2.656	-3.179	-.483	-1.569	-1.288
	2p	.013	.008*	.001*	.629	.117	.198
	N	19	19	19	19	19	19
4.0 m	Z	3.622	-3.300	-3.421	-1.569	-.262	-1.569
	2p	<.001*	.001*	.001*	.117	.794	.117

* Significant after Bonferroni correction. Level of significance $p < .008\overline{3}$.

Table 3.28: Constant error of predicted distance under the I-RCHB, F-RCHB, F-RHC, and F-B conditions (Mean±SD).

	CE predicted distance [m]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	0.82±1.15	-0.07±1.15	-0.78±1.07
F-RCHB	1.12±0.97	0.55±0.94	0.24±1.04
F-RCH	0.89±0.95	0.44±0.98	-0.06±1.04
F-B	1.07±0.86	0.71±1.01	0.34±1.14

Constant error (CE)

The constant error decreases with increasing real putting distance under all full vision conditions (see Fig 3.16 and Table 3.28). While the constant error under the F-RCHB, F-HCB, and F-B conditions decreases comparably, i.e., by 0.88m (F-RCHB), 0.94 (F-RCH) and 0.73 (F-B), the constant error under the I-RCHB condition changes sign from +0.81 to -0.77.

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0, and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) revealed significant main effects of vision condition and distance as well as a significant interaction effect (see Table 3.29).

A follow-up analysis using a Wilcoxon test with Bonferroni correction (see Table 3.30) revealed no significant differences between the vision conditions at the real distances of 2.0 m. For the real distances of 3.0 m significant difference between the I-RCHB and the two manipulated vision conditions (F-RCH and F-B) are revealed. At a distance of 4.0 m there are significant differences between the incomplete (I-RCHB) and the three full (F-RCHB, F-RCH, and F-B) vision conditions.

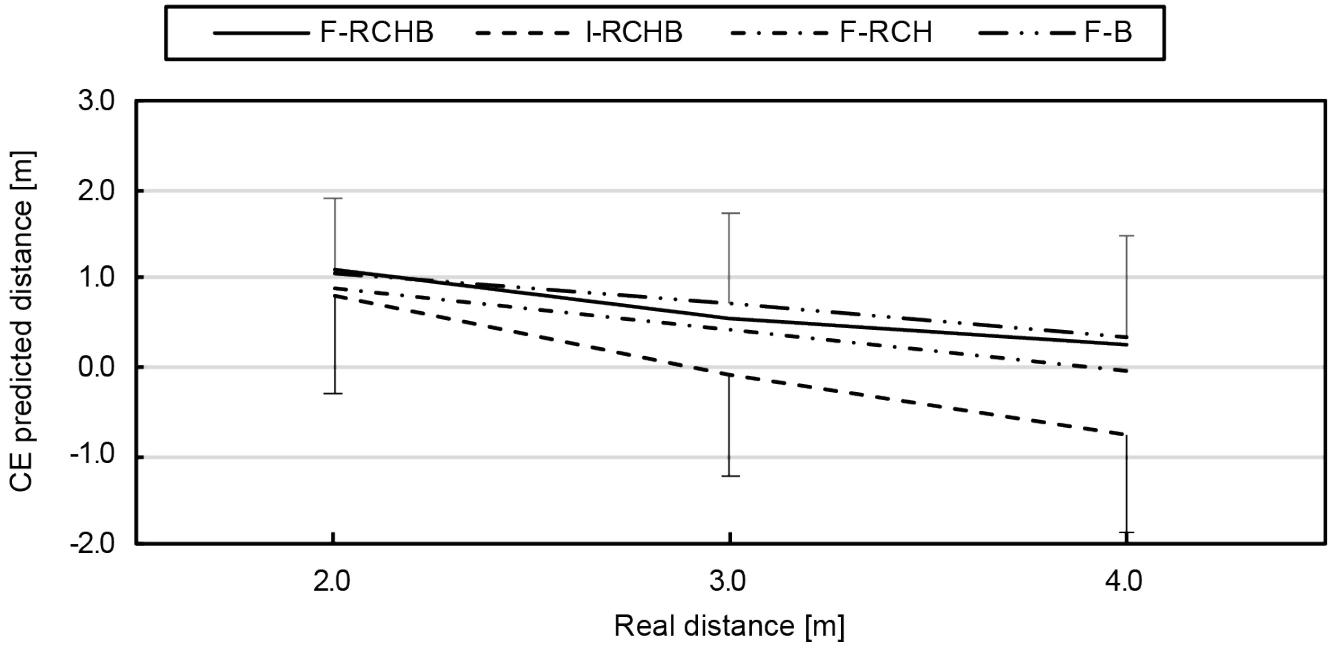

Figure 3.16: Constant error. Mean and standard deviation of the constant error of predicted putting distance under the I-RCHB, F-RCHB, F-RCH, and F-B conditions.

Table 3.29: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the constant error of predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.92	34.50	12.04	$<.001$	.401
Distance	1.59	28.58	72.00	$<.001$	.800
Vision condition x distance	4.56	82.09	4.25	.002	.191

Variable Error (VE)

The variable error under the F-RCHB condition remains approximately constant from short (0.59 m) to medium (0.60 m) distances and increases to 0.70 m for long distances (see Fig 3.17 and Table 3.31). As the only condition, I-RCHB shows a decrease of the variable error from small (0.60 m) to medium (0.55 m) distances with an increase to large (0.65 m) distances. Under condition F-B, the variable error is higher compared to all other conditions for all distances. The variable error increases from short (0.67 m) to medium (0.77 m) distances and decreases for long (0.73 m) distances. An increase from small (0.53 m) to medium (0.67 m) distances of the variable error can also be observed under the F-RCH, the increase continues to large (0.70 m) distances.

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0, and 4.0 m; 4 vision conditions: I-RCHB, F-RCHB, F-RCH, and F-B) revealed no significant main effects of vision condition and distance or interaction effect (see Table 3.32).

Table 3.30: Follow-up analyses (Wilcoxon test and Bonferroni correction) of the interaction of putting distance and vision condition for the constant error of predicted putt length at the real putting distance.

		I-RCHB vs. F-RCHB	I-RCHB vs. F-RCH	I-RCHB vs. F-B	F-RCHB vs. F-RCH	F-RCHB vs. F-B	F-HCB vs. F-B
	N	19	19	19	19	19	19
2.0 m	Z	1.650	-.322	-1.368	-1.408	-.724	-1.127
	2p	.099	.748	.171	.159	.469	.260
	N	19	19	19	19	19	19
3.0 m	Z	2.495	-2.656	-3.179	-.483	-1.569	-1.288
	2p	.013	.008*	.001*	.629	.117	.198
	N	19	19	19	19	19	19
4.0 m	Z	3.622	-3.300	-3.421	-1.569	-.262	-1.569
	2p	<.001*	.001*	.001*	.117	.794	.117

* Significant after Bonferroni correction. Level of significance $p < .008\overline{3}$.

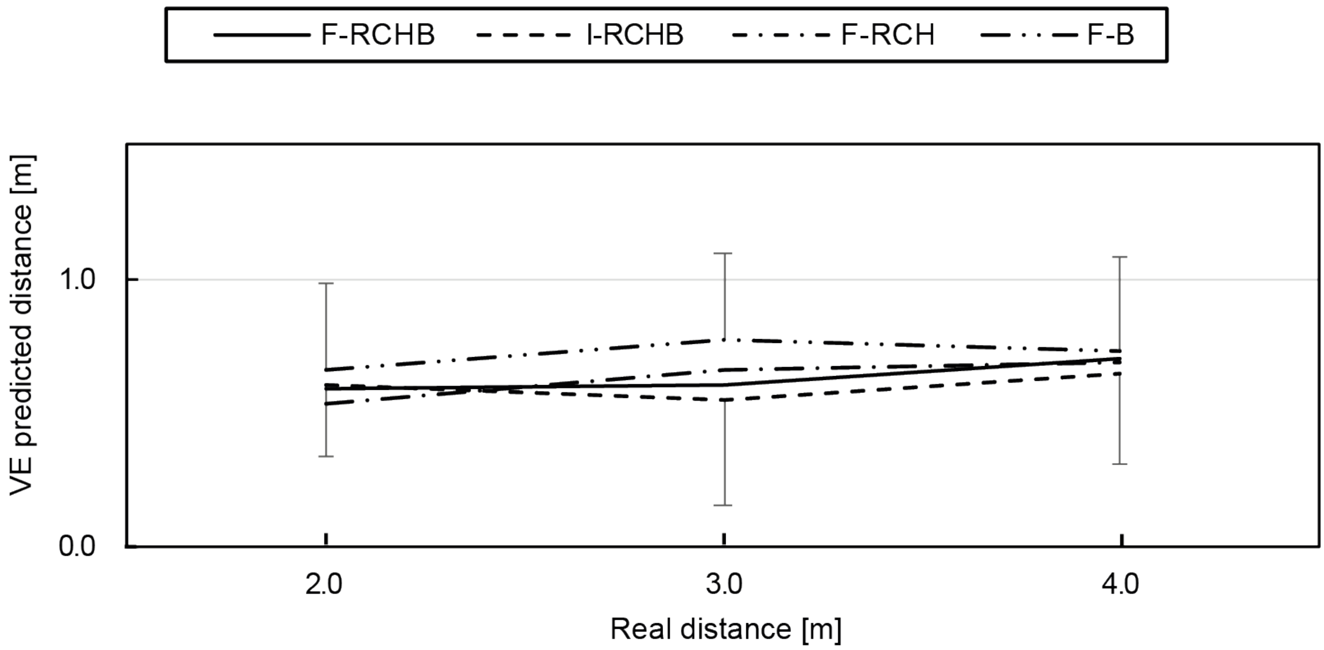

Figure 3.17: Variable error. Mean and standard deviation of the variable error of the predicted putting distance under the I-RCHB, F-RCHB, F-RCH, and F-B conditions.

Absolute Error (AE)

Figure 3.18 and Table 3.33 show a decrease of the absolute error from small to medium distances under all conditions. While under the I-RCHB and F-RCH conditions an increase to large distances follows, the

Table 3.31: Variable error of predicted distance under the I-RCHB, F-RCHB, F-RCH, and F-B conditions (Mean±SD).

	VE predicted distance [m]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	0.60±0.26	0.55±0.38	0.65±0.35
F-RCHB	0.59±0.32	0.60±0.36	0.70±0.44
F-RCH	0.53±0.28	0.67±0.40	0.70±0.30
F-B	0.67±0.31	0.77±0.32	0.73±0.36

Table 3.32: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the variable error of predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p
Vision condition	2.54	45.74	1.35	.271
Distance	2.0	35.93	1.75	.188
Vision condition x distance	3.14	56.53	0.38	.779

absolute error under the F-RCHB and F-B conditions remains approximately constant.

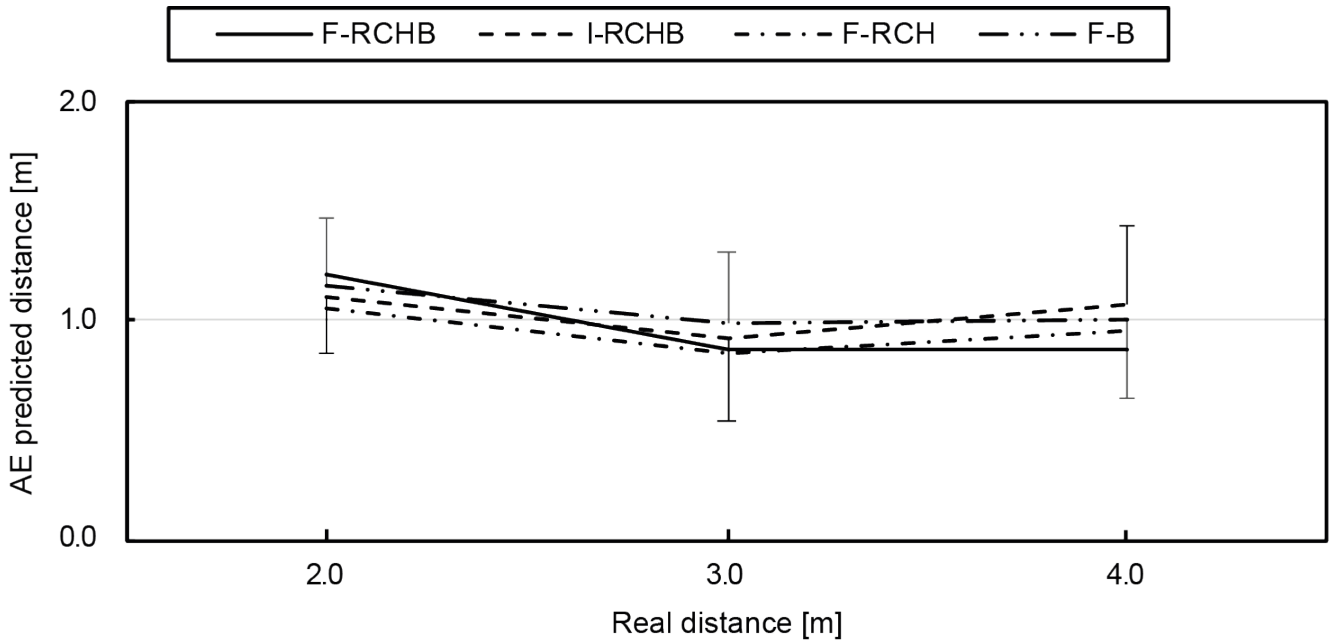

Figure 3.18: Absolute error. Mean and standard deviation of the absolute error of the predicted putting distance under the F-RCHB, I-RCHB, F-RCH, and F-B conditions.

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0, and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) revealed no significant main or interaction effects (see Table 3.34).

Table 3.33: Absolute error of predicted distance under the I-RCHB, F-RCHB, F-RCH, and F-B conditions (Mean±SD).

	AE predicted distance [m]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	1.12±0.82	0.92±0.68	1.07±0.78
F-RCHB	1.22±0.83	0.88±0.64	0.87±0.60
F-RCH	1.06±0.74	0.85±0.65	0.95±0.64
F-B	1.16±0.74	0.99±0.74	1.01±0.63

Table 3.34: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for absolute error of the predicted putt length. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p
Vision condition	2.36	42.39	0.620	.568
Distance	1.42	25.48	2.77	.097
Vision condition x distance	3.66	65.95	0.71	.574

Confidence of prediction

Compared to the other three conditions, the confidence of the prediction under the I-RCHB condition is lowest over all distances (see Table 3.19 and Fig 3.35). For small (2.92) and medium (2.92) distances the confidence remains constant and decreases for longer (2.81) distances. The values under the F-RCH condition are higher than the values under I-RCHB and lower than the values under the other two conditions (F-RCHB and F-B) over all distances. The confidence of prediction slightly increases with increasing distance and approaches the values of the F-RCHB and F-B conditions for large distances. Under the F-B condition the confidence of prediction increases with increasing putting distance. The F-RCHB condition shows the highest confidence of prediction for small and large distances, for medium distances the value (3.27) is slightly below the F-B condition (3.3). The confidence of prediction decreases from small to medium distances and increases again from medium to long distances.

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0, and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) revealed a significant main effect of vision condition (see Table 3.36).

Table 3.35: Confidene of prediction under the I-RCHB, F-RCHB, F-RCH, and F-B conditions (Mean±SD).

	Confidence [1-5]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	2.92±0.67	2.92±0.80	2.82±0.87
F-RCHB	3.38±0.75	3.28±0.78	3.39±0.71
F-RCH	3.03±0.83	3.13±0.78	3.29±0.78
F-B	3.21±0.72	3.30±0.80	3.33±0.81

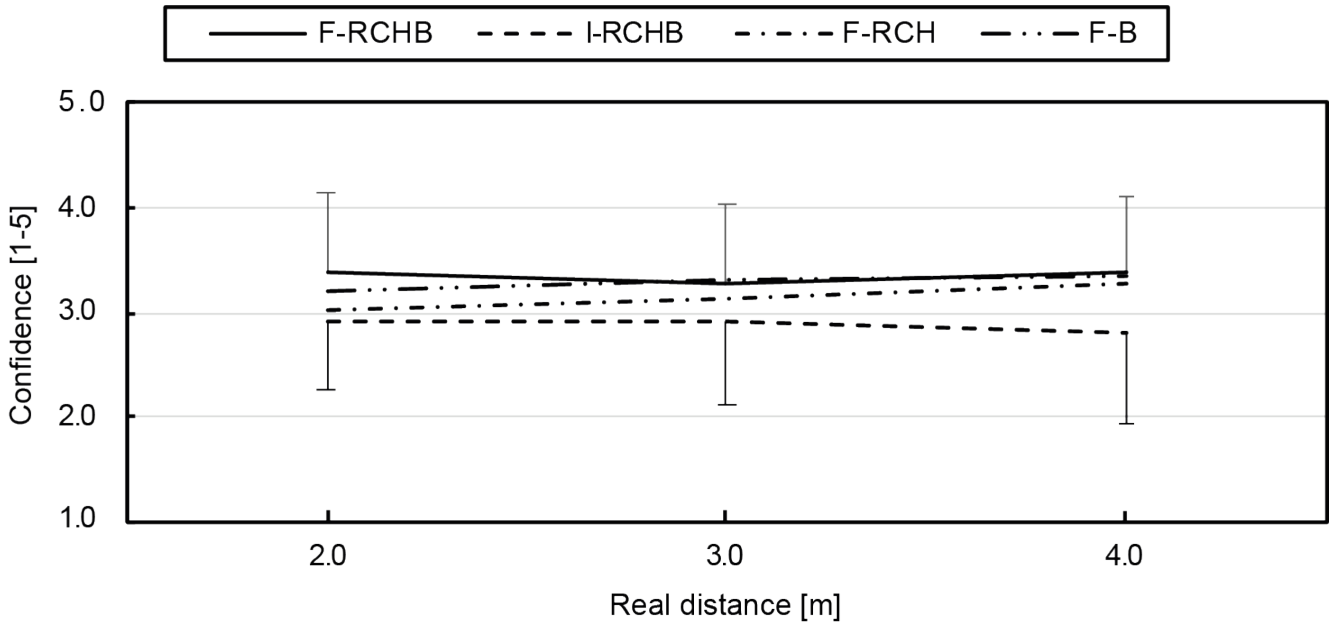

Figure 3.19: Confidence of prediction. Mean and standard deviation of the confidence of prediction depending on the real putting distance under the I-RCHB, F-RCHB, F-RCH, and F-B conditions.

Table 3.36: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the confidence of prediction. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	2.06	36.97	10.87	$<.001$	.376
Distance	1.45	26.15	1.06	.340	.056
Vision condition x distance	3.64	65.55	1.44	.234	.074

A follow-up analysis using a Wilcoxon test with Bonferroni correction (see Table 3.37) revealed significant differences between the F-RCHB and I-RCHB conditions over all distances and between I-RCHB and F-B at the distances of 3.0 and 4.0 m.

Response time

Fig 3.20 and Table 3.38 show the means and standard deviations of the response time of all participants for the three real putting distances under the four experimental conditions. The response times under the I-RCHB and F-B conditions increase with increasing distance, the response time of F-B is on average 0.65 s below the response time of I-RCHB over all distances. Under F-RCHB, the response time for short and medium distances is higher than under the other conditions, but lowest for long distances. The response time is constant for short and medium distances and decreases from medium to long distances. The response time under the F-RCH condition decreases with increasing putting distance from 5.43 s (2.0 m) to 4.84 s (4.0 m).

Table 3.37: Follow-up analyses (Wilcoxon test and Bonferroni correction) of the interaction of putting distance and vision condition for the confidence of predicted putt length at the real putting distance.

		I-RCHB vs. F-RCHB	I-RCHB vs. F-RCH	I-RCHB vs. F-B	F-RCHB vs. F-RCH	F-RCHB vs. F-B	F-HCB vs. F-B
	N	19	19	19	19	19	19
2.0 m	Z	2.919	-.606	-1.911	-2.540	-1.531	-1.252
	2p	.004*	.544	.056	.011	.126	.210
	N	19	19	19	19	19	19
3.0 m	Z	3.024	-2.040	-2.811	-1.342	-.454	-1.785
	2p	.002*	.041	.005*	.180	.650	.074
	N	19	19	19	19	19	19
4.0 m	Z	3.125	-2.621	-2.866	-1.203	-1.204	-.353
	2p	.002*	.009	.004*	.229	.229	.724

* Significant after Bonferroni correction. Level of significance $p < .008\overline{3}$.

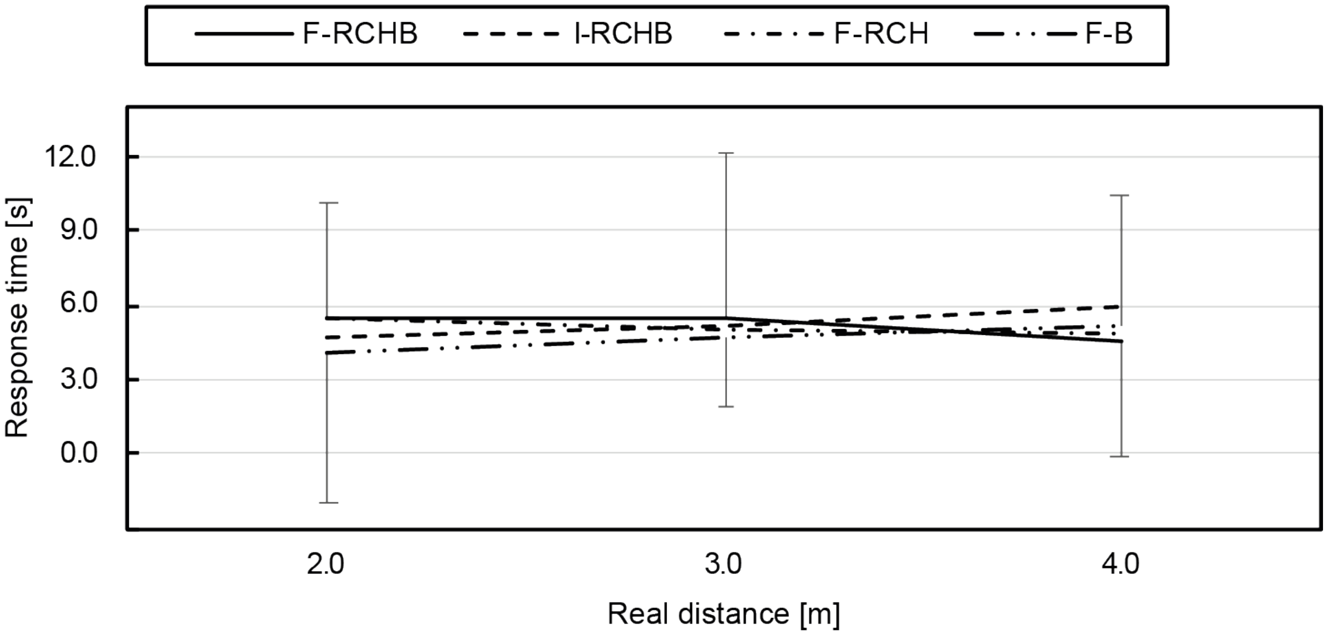

Figure 3.20: Predicted putting distance. Mean and standard deviation of the response time depending on the real putting distance under the I-RCHB, F-RCHB, F-RCH, and F-B condition.

The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0 and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) revealed no significant main or interaction effects (see Table 3.39).

Table 3.38: Response time depending on the real putting distance under the I-RCHB, F-RCHB, F-RCH, and F-B condition (Mean±SD).

	Response time [s]		
Condition	2.0 m	3.0 m	4.0 m
I-RCHB	4.73±3.01	5.14±3.34	5.92±7.11
F-RCHB	5.45±4.73	5.45±6.69	4.57±4.59
F-RCH	5.43±4.71	5.02±3.49	4.85±5.97
F-B	4.07±2.10	4.62±2.75	5.15±5.20

Table 3.39: Results of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the response time. Corrected by Greenhouse-Geisser ϵ.

Factor	df1	df2	F	p	η_p^2
Vision condition	2.40	43.73	1.02	.388	
Distance	1.63	29.39	.183	.790	
Vision condition x distance	3.88	69.84	1.18	.327	

3.5 Discussion and Conclusion

We performed two studies to examine the effect of different viewing conditions on accuracy and precision of estimated/predicted putting distance. Comparing the results (distance, CE, AE, VE, confidences, and response time) both studies show comparable values for the respective variables.

First, study 1 and study 2 reveal a significant over-estimation of putting distance in the full vision conditions. This apparently supports expectations derived from the FLE . However, in contrast to hypothesis 1, prediction error (CE) did not increase, but rather decreased with increasing putting distance. An important difference to the FLE experiments is that under full vision at least one object was still visible after impact. Therefore, this additional information may have destroyed the FLE. In the incomplete condition we also found no increase of prediction error. However, the time of the downswing (0.46 to 0.58 s) may have been too short to allow for valid perception, indicated by CE and confidence. In study 1 the CE values show a linear development and a sign change from short distances (1.11 m at a distance of 2.5 m) to long distances (-0.95 m at a distance of 4.0 m). This represents the tendency of the participants to choose distances in the middle of the distance scale at 3.00 m, regardless of the actual distance of the video sequence. At all distances, the confidence in the incomplete condition (mean = 2.63) is below the confidence in the full condition (mean = 3.22). Overall, hypothesis 1 was not supported by the data of either study.

Furthermore, study 1 reveals significant differences between the predicted putting distance in the full vision (F-RCHB) and the incomplete vision (I-RCHB) condition (see table 3.40). While in the full vision condition the predicted putting distance increases with increasing real distance, in the incomplete motion condition the prediction is nearly constant (2.99±0.09 m) around the mean value of the estimation scale (0.00 to 6.00 m) of 3.00 m (see Fig 3.9 and Table 3.7). In the full motion condition a systematic overestimation of the putt performance by an average of 0.89±0.18 m (mean and standard deviation of the CE) occurs which does not increase with distance (as was expected in hypothesis 1). In the incomplete motion condition, however, the CE shows a change in sign due to the constant prediction around the mean value of the estimation scale and thus a lower mean value of 0.24±0.09 m. Study 1 revealed that a valid prediction of the putting distance in the incomplete motion condition is not possible and instead a tendency towards the middle of the estimation scale occurs. This assumption is supported by results of the VE and AE. In both cases there are no significant differences between the two conditions. The prediction of the putting distance shows a constant variability under both conditions. This supports the assumption that a prediction of the distance under the incomplete condition is not possible and that the participants tend to be in the middle of the evaluation scale. The comparable level of the AE can also be explained by the constant overestimation of the putting distance in the full vision condition and the tendency towards the middle of the distance scale (at 3.00 m) in the incomplete condition. The confidence of the prediction of the putting distance also shows significant differences between the two conditions depending on the real putting distance (see Fig 3.13 and Table 3.17). The prediction of the putting distance in the incomplete motion condition is rated less confident than in the complete condition (mean difference: 0.59 over all distances). The evaluation of the confidence of the prediction supports hypothesis 2 that in the incomplete motion condition a prediction of the putting distance is not possible. Significant differences between the two conditions are also apparent in the response time. Over all distances, the response time in the incomplete motion condition is on average 0.93 s higher than in the complete motion condition, again supporting hypothesis 2. The results of study 1 for the prediction of the putting distance, the constant error, the variable error, the absolute error and the confidence of the prediction could be replicated in study 2. Therefore, hypothesis 2 was confirmed. Comparable courses of the prediction of the putting distance (see Fig 3.15 and Table 3.25), the CE of the prediction (see Fig 3.16 and Table 3.28) and the confidence of the prediction (see Fig 3.19 and Table 3.35) were found. However, hypothesis 2 could not be replicated regarding response time. While in study 1 the response time in the full motion condition is always shorter than in the incomplete motion condition, in study 2 it is only consistently shorter in the F-B compared to the I-RCHB condition. The results of the two studies, which are consistent with regard to the prediction and the confidence of the prediction, confirm the assumption that the prediction of the putting distance by the human observer is more accurate, more confident and – with some limits - faster when the full motion is shown (hypothesis 2). The follow-through phase of the putt movement has an important influence on the prediction of putt performance. However, hypothesis 1 (increasing errors with increasing putting distance) could not be confirmed in either studies.

Table 3.40: Overview of significant differences in study 1 and 2.

	Study 1			Study 2		
Parameter	VC	D	VC x D	VC	D	VC x D
Estimated distance	X	X	X	X	X	X
Constant error	X	X	X	X	X	X
Variable error						
Absolut error						
Confidence	X			X		
Response time	X					

VC = Vision condition; D = Distance.

The differences in accuracy expected in Study 2 in predicting the putting distance between the condition with full vision (F-RCHB) and/or restricted visions, invisible ball (F-RCH) or club and robot (F-B) cannot be confirmed (hypothesis 3). Significant differences can only be demonstrated between the three full conditions and the incomplete condition (I-RCHB). Furthermore, the vision of the ball is not mandatory since the F-RCH condition showed a tendency towards higher accuracy (CE and AE). On the other hand, the invisibility of club, club head and robot seems to be compensated by the vision of the ball. However, the F-RCH condition showed a tendency to be more accurate (estimated distance and CE) than the other full conditions and – with the exception of 4 m distance - the F-B condition resulted in faster response times compared to the other full conditions.

Ex post power analysis regarding hypothesis 2 reveal that both studies are "overpowered" for the factors predicted distance (power: study 1 = 1.0; study 2 = 0.999), CE (power: study 1 = 1.0; study 2 = 0.999) and confidence (power: study 1 = 1.0; study 2 = 0.999), see S1 File and S2 File. Therefore, the assumed overestimation of the effect size according to the "winner's curse phenomenon" Button et al., 2013 from study 1 was not confirmed in the results of study 2. Following Zhang and Hughes Zhang and Hughes, 2020, a subgroup analysis was carried out. The populations of both studies were divided into two subgroups (group 1: without previous experience; group 2 = with previous experience) based on the mentioned previous experience in golf, field field hockey and similar sports. In study 1, 10 participants reported that they had experience in golf or similar sports, 10 participants reported that they had no previous experience. In study 2, 8 participants reported that they had experience in golf or similar sports, 11 participants reported that they had no previous experience. The two-factor ANOVAs with repeated measures were calculated with regard to hypothesis 2 for both studies. Table 3.41 provides an overview of significant differences in the two studies.
The two-factor ANOVA with repeated measures (6 distances: 1.5, 2.0, 2.5, 3.0, 3.5, 240 and 4.0 m; 2 vision conditions: full and incomplete vision) for group 1 in study 1 revealed significant main effects of vision condition and distance and no significant interaction effect for the predicted distance and CE. For group 2, significant main effects of vision condition and distance and significant interaction effects were revealed for the predicted distance and the CE. Both groups show significant effects of the vision condition for the confidence (for details see S1 Table). The two-factor ANOVA with repeated measures (3 distances: 2.0, 3.0 and 4.0 m; 4 vision conditions: F-RCHB, I-RCHB, F-RCH, and F-B) for group 1 revealed significant main effects of vision condition and distance and significant interaction effect for the variables predicted distance and CE. For group 2 significant main effects of vision condition and distance and no significant interaction effects were revealed for the predicted distance and the CE. Both groups show significant effects of the vision condition for the confidence (for details see S1 Table). Again, the calculated power analyses regarding the two subgroups revealed consistent overpowerment (with three exceptions: study 1 – group 1 and 2 regarding interaction of vision condition and distance for confidence; study 2 – group 2 regarding interaction of vision condition and distance for confidence).

With regard to the possible spatio-temporal information during the putt motion, indications in the down-swing phase ($t_{downswing}$ and $V_{C\text{-}impact}$) do not seem to have specific significance to the prediction of putt performance. To test the assumption that the upswing phase has a preparatory function for the perception of the follow-through phase, e.g. eye movement, an isolated study on the influence of the downswing phase on the quality of the prediction of putt performance must be conducted. In the follow-through phase in particular, the duration of the phase seems to be an important indication of the putt length. Further spatio-temporal information, e.g. the ball velocity after the impact ($V_{B\text{-}impact}$), the movement of club and ball and X ($ball_{x\ follow\text{-}through}$ and $club_{x\ follow\text{-}through}$) and Y ($ball_{y\ follow\ through}$ and $club_{y\ folloe\text{-}through}$) direction, as well as the radial distance between club head and ball (rd) do not seem to have a decisive influence on the quality of the prediction. The mentioned spatio-temporal information probably provides redundant information for the human observer.

Based on the results of the two presented studies, future studies should investigate the influence of different

Table 3.41: Overview of $\eta^2{}_p$, significant, and power of the subgroup analyses in study 1 and 2 .

		Study 1		Study 2	
Subgroup	Parameter	VC	VC x D	VC	VC x D
No golf experience	Predicted distance	$\eta^2{}_p$ = .605 * power = 1.0	$\eta^2{}_p$ = 0.703 * power = 1.0	$\eta^2{}_p$ = .99 * power = 1.0	$\eta^2{}_p$ = .99 * power = 1.0
	Constant error	$\eta^2{}_p$ = .605 * power = 1.0	$\eta^2{}_p$ = .703 * power = 1.0	$\eta^2{}_p$ = .639 * power = 1.0	$\eta^2{}_p$ = .639 * power = 1.0
	Confidence	$\eta^2{}_p$ = .804 * power = 1.0	$\eta^2{}_p$ = .129 power = .722	$\eta^2{}_p$ = .987 * power = 1.0	$\eta^2{}_p$ = .403 power = .999
Golf experience	Predicted distance	$\eta^2{}_p$ = .686 * power = 1.0	$\eta^2{}_p$ = 0.681 * power = 1.0	$\eta^2{}_p$ = .626 * power = .999	$\eta^2{}_p$ = .415 power = .927
	Constant error	$\eta^2{}_p$ = .686 * power = 1.0	$\eta^2{}_p$ = .681 * power = 1.0	$\eta^2{}_p$ = .415 * power = .999	$\eta^2{}_p$ = .99 power = .927
	Confidence	$\eta^2{}_p$ = .573 * power = 1.0	$\eta^2{}_p$ = .102 power = .537	$\eta^2{}_p$ = .9 * power = 1.0	$\eta^2{}_p$ = .206 power = .557

VC = Vision condition; D = Distance; * $p < .05$.

spatio-temporal information in the follow-through phase on the quality of the prediction of the putting distance. The first step is the clarification which elements of the robot putting motion, e.g. ball or club, the human observers pay attention to. The use of an eye-tracking system to record the direction of gaze during the presentation of the individual video sequences represents a feasible approach. In addition, the spatio-temporal information of the follow-through phase should be further differentiated, e.g. various combinations of non-visible robot, club, club head and ball. The ball and the individual elements of the robot-club system, e.g. robot-arm, club, and club head, often represent the same spatio-temporal information, e.g. club head and robot arm move at the same angular velocity. It is possible that this redundant information has a disruptive influence on the evaluation of the putting performance.

The influence of prior experience in different sports, computer games and golf itself on the prediction of putting performance has to be further investigated. For this purpose, the data already collected provide a basis and should be extended by a group of golf experts, e.g. golf instructors.
Another important extension of the experiments is to test further performance-related parameters to be estimated, e.g., velocity of club and ball at impact, since the distance estimation is outcome-related. This would closer resemble the human-robot interaction where humans have to estimate further performance-related features of robot motion. It is also important to distinguish between absolute judgment and relative judgments. In particular the relative judgments, e.g. slower vs. faster, shorter vs. longer and others are of great importance in a dyadic movement learning process. In the dyad movement learning behavior of human-human dyads, relative judgments and descriptions are often used as feedback, e.g. swing the club more slowly. The further investigation of the transferability of this feedback strategy to human-robot dyads represents an approach to optimize the movement learning process between humans and robots.

3.6 Supporting information

S1 Video. 2.00 m robot putt in F-RCHB. Exemplary video sequence of a robot putt with a putting distance of 2.00 m in the full vision condition with visible robot, club, club head, and ball (F-RCHB) in the follow-through phase. (MP4)

S2 Video. 2.00 m robot putt in I-RCHB. Exemplary video sequence of a robot putt with a putting distance of 2.00 m in the incomplete vision condition with visible robot, club, club head, and ball (I-RCHB) in the follow-through phase. (MP4)

S3 Video. 2.00 m robot putt in F-RCH. Exemplary video sequence of a robot putt with a putting distance of 2.00 m in the full vision condition with visible robot, club, and club head. (F-RCH) in the follow-through phase. (MP4)

S4 Video. 2.00 m robot putt in F-B. Exemplary video sequence of a robot putt with a putting distance of 2.00 m in the full vision condition with visible ball (F-B) in the follow-through phase. (MP4)

S1 Dataset. Dataset study 1. data set of study 1 with the recorded (video sequence number, predicted distance, confidence, and response time) and calculated (constant error, variable error, and absolute error) values (XLSX).

S2 Dataset. Dataset study 2. data set of study 2 with the recorded (video sequence number, predicted distance, confidence, and response time) and calculated (constant error, variable error, and absolute error) values (XLSX).

S1 File. Power calculation 1. G*Power calculation protocol for study 1 (PDF).

S2 File. Power calculation 2. G*Power calculation protocol for study 2 (PDF).

S1 Table. Detailed results of the subgroup analysis. Results of the two-factor ANOVA with repeated measures (6 distances; 2 vision conditions) for the predicted distance, the CE and the confidence for the two subgroups in study 1 and of the two-factor ANOVA with repeated measures (3 distances; 4 vision conditions) for the predicted distance, the CE and the confidence for the two subgroups in study 2. Corrected by Greenhouse-Geisser ϵ (PDF).

3.7 Acknowledgments

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4 Artikel III: Visual Perception of Robot Movements–How Much Information Is Required?

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Abstract

Human-robot interactions are steadily increasing in all areas of life. In this context, a common motion learning process of human-robot dyads has not been studied so far.

The observation of movement characteristics plays a crucial role in the assessment and learning of movements in human-human dyads. But what visual information of a robot movement can be perceived and predicted by humans?

The following study examines the perception and prediction of robot putt movements by humans with different visual stimuli. Relevant clues could be identified for the specific movement. Ultimately, with sufficient visual information, humans are able to correctly predict the outcome of a robot putt movement.

4.1 Introduction

In recent years, the number of human-robot interactions has increased in numerous areas, e.g. in rehabilitation, in industry or in sport. While robots and humans are often assigned to separate areas, the overlap of work spaces between robots and humans is constantly growing. An important question is how robots and humans can work together effectively. In an ideal cooperative scenario, the perceptions and actions of humans and robots are perfectly matched. In this article we focus on human perception of robot movements.

Numerous studies have shown that even with few stimuli humans are able to perceive and classify biological movements (Orgs et al., 2011). Based on these results, Runeson developed the "Kinematics Specify Dynamics" Principle (Runeson and Frykholm, 1983; Tremoulet and Feldman, 2000). Ballreich (1983) was able to show that the kinematics and kinetics of a jump movement could be correctly classified, but not the joint angles. Cañal-Bruland and Williams (2010) report evidence that distal cues, e.g. motion of the raquet, play an important role in predicting the directions of tennis strokes. Until now, the transferability of the findings for the evaluation of biological movements to non-biological movements has not been considered.

The following study examines how the prediction of the putt length depends on the visibility of various elements of the robot putt, e.g. ball, parts of the robot or club. Depending on the visible elements, different kinematic cues for estimating the robot putt and the resulting putt distances are available to the human observer: First, the speed of movement of robot, club and ball. Second, the speed has a direct impact on the distance the ball and clubhead travel, and the radial distance between them. Third, the duration of the shown video sequences. Due to the higher ball speeds, the duration of the video sequences decreases with increasing putt distance.

4.2 Materials and Methods

The following describes the method used in the study which is divided into three substudies. The sub-studies differ in the presented video sequences.

4.2.1 Participants

Thirty healthy students (22 males and 8 females), aged 18–26 years, volunteered to participate in three sub-studies. Inclusion criteria was no previous experience with perceptual studies. Demographic data are presented in Table 4.1 & 4.2.

Table 4.1: Individual participants characteristics (Mean±SD) of the sub-studies (sub).

	N	Gender [f|m]	Age [years]	Height [cm]	Bodymass [kg]	Handedness [left|right]
sub 1	10	1|9	20.4±1.8	170.2±6.3	76.3±9.8	0|10
sub 2	10	0|10	24.1±1.5	181.9±6.0	78.9±10.2	1|9
sub 3	10	7|3	22.6±2.0	170.9±13.0	64.0±17.9	2|8
Total	30	8|22	22.3±2.3	177.4±9.9	73.0±14.3	3|27

Table 4.2: Previous experience in golf, returning games, ball games and computer games.

	Previous experience			
	Golf	Returning Games	Ball games	Computer games
sub 1	0	4	8	8
sub 2	0	1	6	5
sub 3	1	6	5	5
Total	1	11	19	18

All participants documented their experience (years of exercising and volume in hours per week) in four different groups of activities:

(1) golf, hockey and similar;

(2) returning games, i.e. tennis, volleyball;

(3) ball games, i.e. soccer, basketball;

(4) computer-games.

Table 4.3 & 4.4 shows the information provided by subjects regarding their previous experience.

Table 4.3: Experience in years (y) and hours per week (h/w) in selective sports and computer games (Mean±SD) per sub-study (sub). Note: Means and SD were only calculated for participants reporting experience.

	Golf, field hockey and similar			Returning games		
	n	years	h/wk	n	years	h/wk
sub1	0	–	–	4	1.0±1.6	0.9±1.2
sub2	0	–	–	1	0.9±2.8	0.1±0.3
sub3	1	3.0±0.0	1.3±1.1	5	2.3±4.1	1.4±1.6
total	1	3.0±0.0	2.0±0.0	11	3.5±3.3	2.0±0.7

Table 4.4: Experience in years (y) and hours per week (h/w) in selective sports and computer games (Mean±SD) per sub-study (sub). Note: Means and SD were only calculated for participants reporting experience.

	Ball games			Computer games		
	n	years	h/wk	n	years	h/wk
sub1	8	11.5±6.8	3.8±2.6	8	7.5±5.7	4.0±4.4
sub2	6	5.9±6.9	2.5±2.4	5	6.8±7.3	3.7±6.2
sub3	5	2.3±4.1	1.4±1.6	5	5.2±7.2	0.9±1.2
total	19	10.3±6.1	4.0±1.7	18	10.8±5.1	4.7±5.1

4.2.2 Apparatus and Task

As a technical platform for the studies, a BioRob robot arm is used (Fig. 4.1). This system has four elastically actuated joints. Each joint is connected via four elastic springs with a separate actuator for each joint. The BioRob system was developed specifically for the physical interaction with humans. Due to its lightweight construction the system generates low kinetic energy. The system is safe to use without collision detection. In order to adapt the system to the anthropometric properties of participants, the BioRob arm was attached to a special lightweight frame. This allows easy adjustment of the height and orientation of the robot arm (Kollegger et al., 2016; Lens et al., 2010; Lens and von Stryk, n.d.).

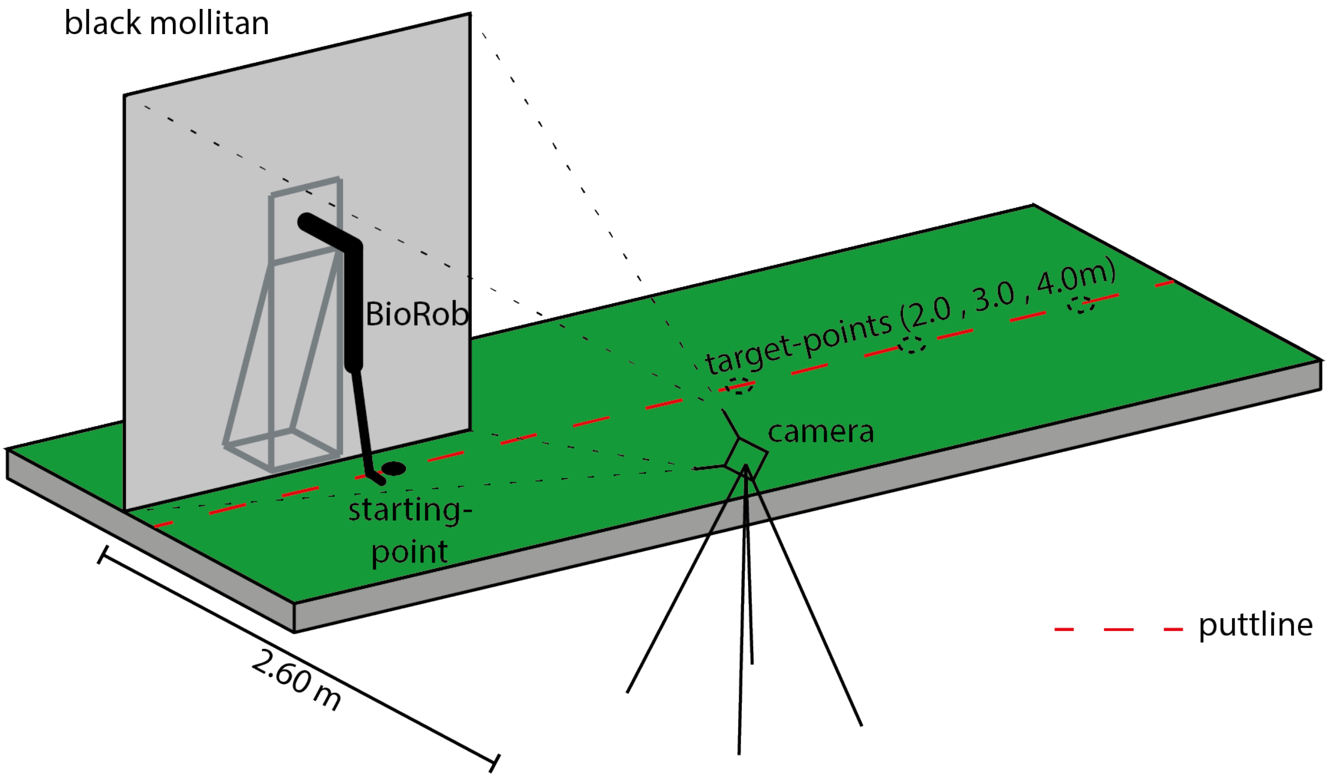

Figure 4.1: Schematic representation of technical arrangement for the recording of the video material.

In order to enable a reproducible robot putt and a uniform rolling behavior of the golf balls an artificial putting green was constructed (Fig. 4.1). The platform is six meters long and two meters wide. The surface consists of a short-pile carpet (Kollegger et al., 2016; Poolton et al., 2006).

The robot putting movements over 3 different putt distances (2.0, 3.0 and 4.0 m) on an artificial putting green were recorded with a Camcorder (Sony FDRAX33) with 50 frames per second. The camera was positioned at a distance of 2.6 m to the ball, perpendicular to the putting direction. As a background, a black mollitan was used, which also covered the mounting frame of the BioRob system (Fig. 4.1).

The presented video material was produced with Adobe Creative Cloud Premiere Pro CC 2018 (Version 12.0.0). All 12 video scenes had the same basic structure:

1. Preliminary phase: 3 s black screen and two short beeps (duration 0.05 s) after one and two seconds followed by a 1 s freeze frame of the robot in the starting position with a fixation cross centered on the handle and a 1 s beep;
2. Backswing phase: identical motion sequence from starting position to reversal point (duration 0.52 s). Regardless of the putt distance, speed, joint angle, and reversal point were kept constant to avoid spatial cues in this phase;
3. Downswing phase: putt-distance-dependent acceleration profiles from reversal to impact;
4. Follow-through-phase: rolling ball and club motion from impact until the ball passes the right boundary of the image.

For presentation of stimuli the spatial and temporal occlusion technique was deployed Wilkins, 2015. In the processed video material, various areas were removed. Each of the three distances was displayed in six different conditions: full video (F-RCHB), hidden robotic arm (F-CH), hidden robot arm and club shaft (F-HB), each in a version with and without ball visible (F-RCH, F-CH & F-H). Four of the six visual conditions were assigned to each sub-study (Table 4.5).

Table 4.5: Assignment of the six conditions to the three sub-studies. Conditions: full video with (F-RCHB) and without visible Ball (F-RCH), hidden robotic arm with (F-CHB) and without visible Ball (F-CH) & hidden robot arm and club shaft with (F-CB) and without visible Ball (F-B).

	Condition					
	F-RCHB	F-RCH	F-CHB	F-CH	F-HB	F-H
sub-study 1	X	X			X	X
sub-study 2			X	X	X	X
sub-study 3	X	X	X	X		

The video sequences were presented by a self-developed computer program. Video clips were displayed by a projector (EPSON EB-1860, resolution: 1024 x 768 px) at the end of the artificial putting green in original size. The projected image of the BioRob system was measured and the projector was set to represent its real size of 1.42 m. Participants watched the video sequences from a distance of 3 m while sitting at a table (Fig. 4.2).

Each of the 12 video sequences per sub-study were shown four times in randomized order (total of 48 clips). Upon completion of each sequence, a visual continuous analog scale (from 0 to 6 m) was presented to the participants to document their length prediction by clicking on the respective value on the scale with

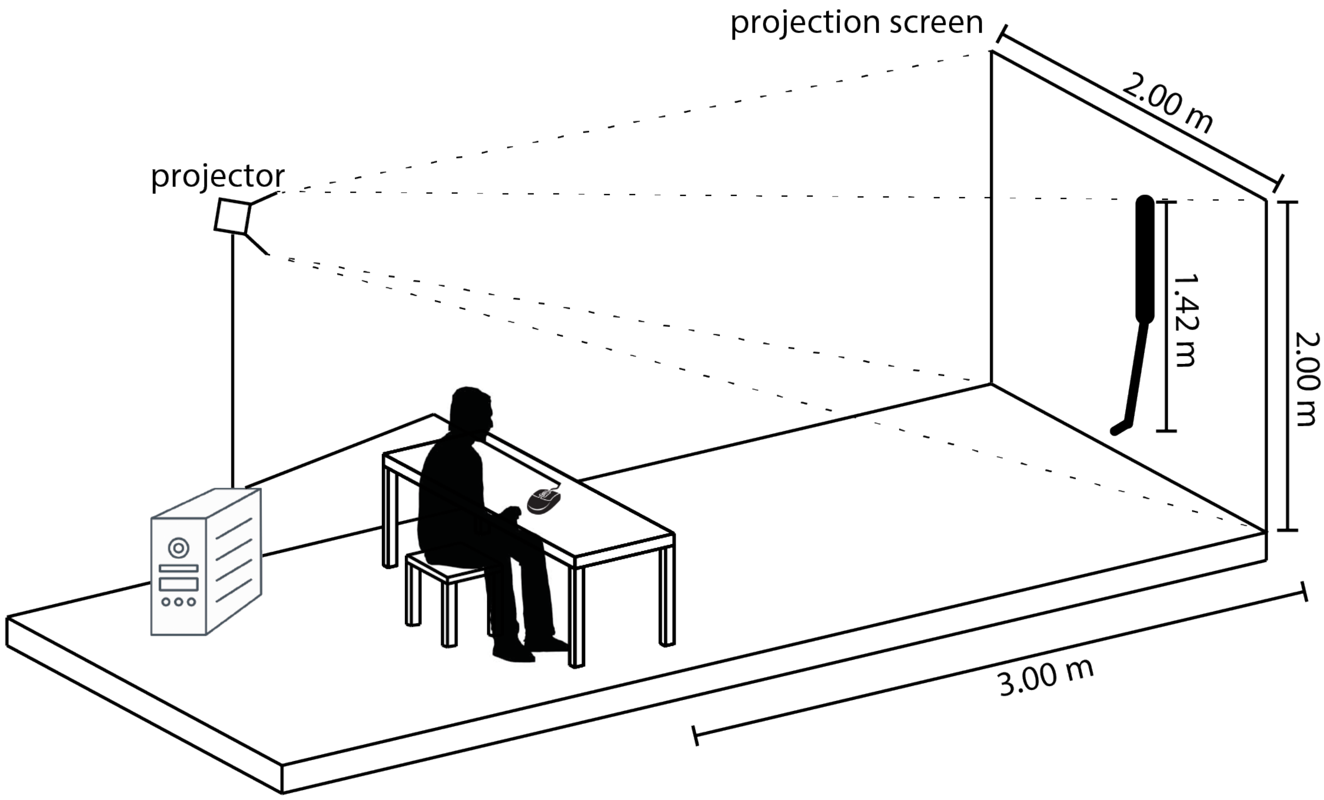

Figure 4.2: Schematic representation of the experimental setup with the projection screen and the position of the participant.

an accuracy of 0.01 m. Following this prediction, participants rated the confidence of their decision on a fivepoint scale (very unsure, unsure, undecided, sure, very sure).

In addition to the assessment of the putt distance and the confidence, the response/decision time, i.e. time elapsed between the end of the video presentation and the final click on the scale, was also recorded. After assessment, the next video was started by clicking a button. All data was stored by the computer program in one file for each participant.

4.2.3 Procedure

First, the participants were introduced to the laboratory and the experimental setup by the experimenter. After this introduction, all participants received an informed consent document and a participant questionnaire. After signing the consent and completing the questionnaire, the test software was presented to the subjects and the experimental procedure was described. The participants read the instructions and questions were answered by the experimenter.

After the introductory phase, the participants started the actual experiment autonomously according to the procedure explained in the previous section. After completion of the test program the participants were debriefed.

4.2.4 Data Processing and Analysis

For each sub-study, a separate two-way ANOVA with repeated measures was calculated with SPSS (V25) with the two factors putt distance (3 distances) and viewing condition (4 conditions). Wilcoxon tests were applied for follow-up analysis. Bonferroni corrections were applied to multiple comparisons. Level of significance was set a priori to 0.05.

4.3 Results

The results of the predicted putt distance in a condensed form, are presented below. In addition to a descriptive presentation, the results of the ANOVA are also shown. For reasons of clarity, the results of the distance prediction of the three sub-studies are summarized.

Means and standard deviations of the predicted putt distance for the three real putt distances with visible (Fig. 4.3) and invisible ball (Fig. 4.4) are illustrated. Short distances are overestimated, whereas long distances are underestimated.

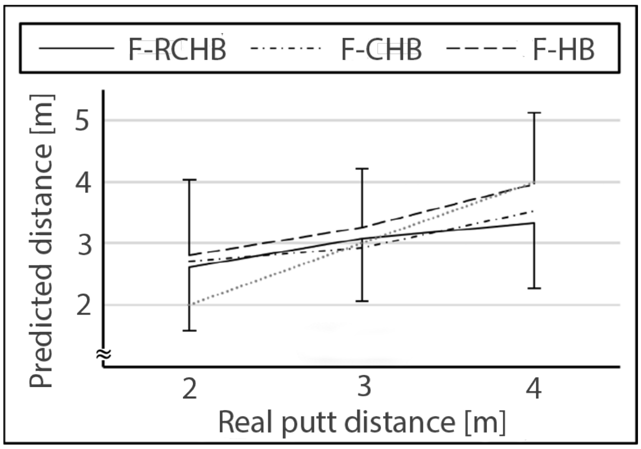

Figure 4.3: Real vs. predictet distance in the conditions with ball visible (F-RCHB, F-CHB & F-HB).

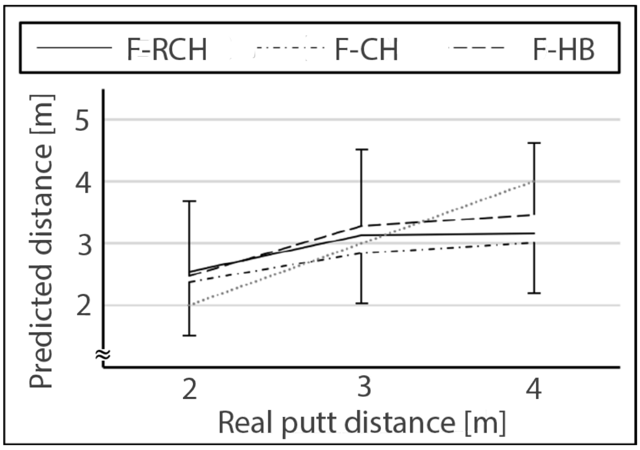

Figure 4.4: Real vs. predictet distance in the conditions with ball invisible (F-RCH, F-CH & F-B).

The predicted distance with the ball visible increases with increasing real distance. The predicted distance in the three conditions with ball invisible increases initially, but remains rather constant between 3 and 4 m at a level of 2.84 to 3.45 m.

The two-way ANOVA with repeated measures revealed significant main effects of distance (all groups), viewing condition (sub-studies 1 & 2) and interaction (sub-study 2), see Table 4.6, 4.7 & 4.8.

Wilcoxon follow-up analyzes showed consistent differences for the assessment of the putt distance between conditions with and without visible ball, see Fig. 4.5. Especially for the distances of 3 and 4 m.

Table 4.6: Results of the 3 distances (2, 3 & 4 m) 4 viewing conditions ANOVA with repeated measures for sub-study 1.

Factor	df1	df2	F	p	η_p^2
Vision condition	3	27	9.66	<.001	.518
Distance	2	18	24.431	<.001	.731
Vision condition x distance	6	54	.235	.963	.025

Table 4.7: Results of the 3 distances (2, 3 & 4 m) 4 viewing conditions ANOVA with repeated measures for sub-study 2.

Factor	df1	df2	F	p	η_p^2
Vision condition	3	27	28.538	<.001	.760
Distance	2	18	43.721	<.001	.829
Vision condition x distance	6	54	.235	<.001	.330

Table 4.8: Results of the 3 distances (2, 3 & 4 m) 4 viewing conditions ANOVA with repeated measures for sub-study 3.

Factor	df1	df2	F	p	η_p^2
Vision condition	1.699	15.295	9.18	.405	.093
Distance	2	18	15.750	<.001	.636
Vision condition x distance	6	54	1.437	.218	.138

4.4 Discussion and Conclusion

The results of the presented study support the current findings regarding the significance of kinematic information, in particular cues derived from the relation of club head and ball movement, e.g. radial distance. The prediction of the putt distance was superior in all conditions with visible ball compared to the conditions without visible ball. These results confirm the special significance of the ball or the relation of club head and ball movement. The robot arm and club shaft do not appear to have a direct impact on the quality of the prediction – possible distractive effect. The reported results are preliminary. Before conclusions can be drawn regarding further studies with adapted optical stimuli, e.g. hidden club head and completely hidden club with visible ball, the respective error scores (AE, CE, VE) must be analyzed (Schmidt and Lee, 1988).

The results confirm previous studies (Kollegger, Wiemeyer, Ewerton, and Peters, 2019): The putt distance of a robot putt can be predicted by humans based on visual information. In addition, the visibility of the ball has a strong influence on distance prediction. The combination of robot, club and ball adds extra cues to the putt distance, e.g. the variation of the radial distance between the ball and the clubhead at different distances.

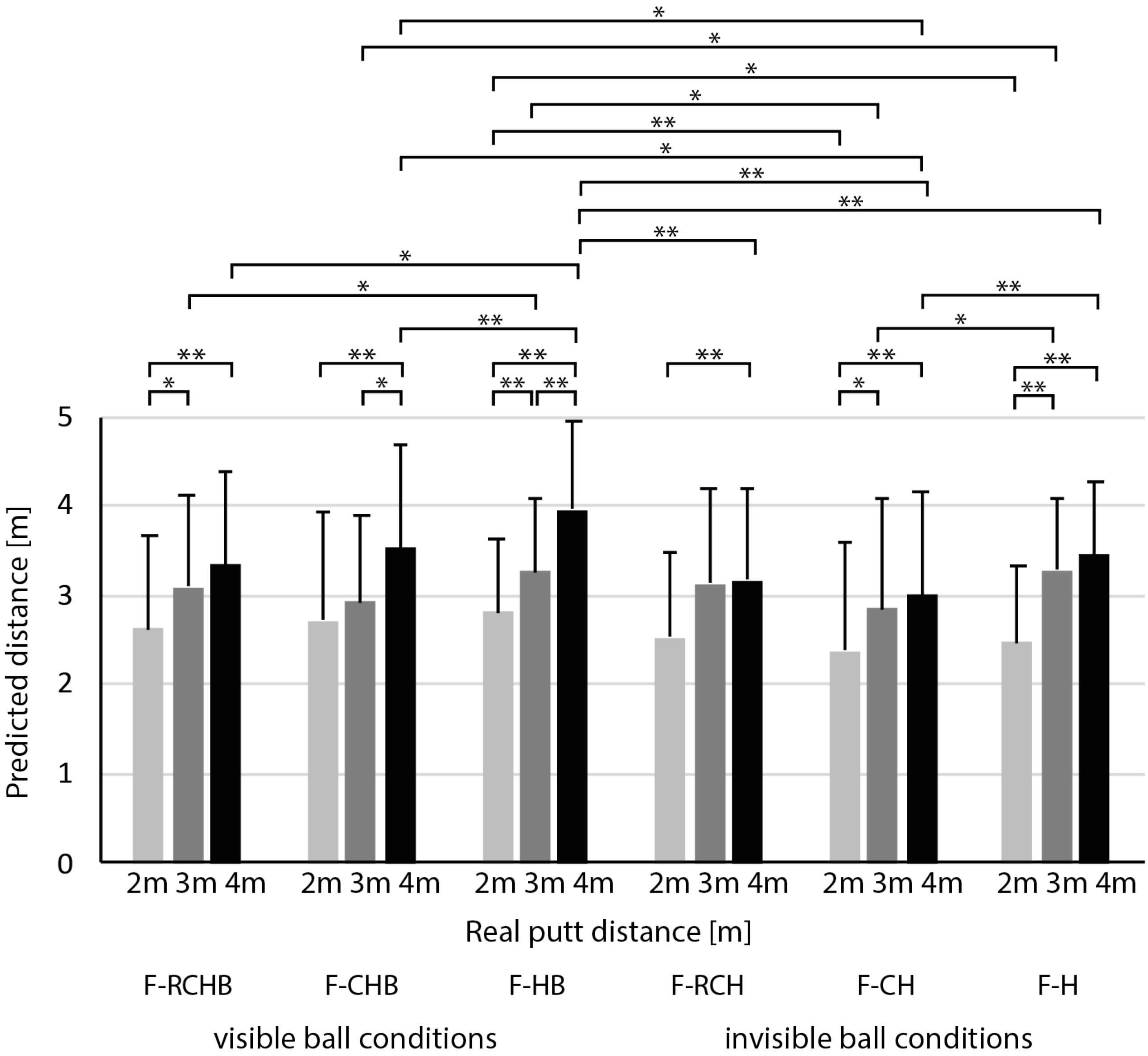

Figure 4.5: Results of follow-up analysis for the factors distance and condition.

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5 Zusammenfassung und Diskussion

In diesem Kapitel werden die wichtigsten Erkenntnisse der vorgestellten Artikel erörtert und in ein größeres Gesamtbild eingeordnet. Weiterhin werden die Grenzen dieser Arbeit diskutiert und zukünftige Forschungsrichtungen dargestellt.

5.1 Wahrnehmung von Roboterbewegungen

Im ersten Teil des Kapitels werden die Erkenntnisse mit Bezug zur visuellen Wahrnehmung von Roboterbewegungen zusammengefasst und diskutiert. Diese Thematik deckt den dritten Strukturbereich des BIMROB-Projekts (siehe Abbildung 1.1) ab und befasst sich mit dem Lernen eines Menschens von einem Roboter, im Speziellen mit der visuellen Wahrnehmung von Roboterbewegungen.
Es schließt sich eine Zusammenfassung der Erkenntnisse ohne direkten Bezug zur visuellen Wahrnehmung von Roboterbewegungen und deren Diskussion an. Die Erkenntnisse sind den Strukturbereichen der bidirektionalen Interaktion zweier Menschen und der unidirektionalen Mensch $\rightarrow$ Roboter-Interaktion (der Roboter lernt vom Menschen) des BIMROB-Projekts zuzuordnen (siehe Abbildung 1.1).

5.1.1 Einfluss der Beobachtungsperspektive

Bezugnehmend auf die Ergebnisse von Ishikura und Inomata (1995) wurde erwartet, dass die Beobachtung der Roboterputtbewegung aus der frontalen Perspektive Vorteile gegenüber der Beobachtung aus der sagittalen Perspektive aufweist.
Die beiden Versuchsgruppen konnten ihre Puttleistung vom Pre- zum Posttest steigern. Entsprechend der Annahme, dass die Beobachtungsperspektive der Frontal-Gruppe Vorteile gegenüber der Sagittal-Gruppe aufweist, sollten die Probanden der Frontal-Gruppe eine größere Leistungssteigerung aufweisen.
Die Ergebnisse zeigen für die Frontal-Gruppe eine Leistungsverbesserung von 17.1 %. Eine größere Leistungssteigerung zeigt die Sagittal-Gruppe mit 22.8 %. Die Unterschiede zwischen den Gruppen werden nicht signifikant. Die Annahme muss zurückgewiesen werden. Für diesen unerwarteten Effekt lassen sich mehrere Gründe formulieren. Die Studie ist mit 32 Probanden underpowered ($1 - \beta = 0.38$). Eine nachträgliche Power-Berechnung ergab, dass an der Studie 81 Probanden teilnehmen müssten. Mit nur sieben Versuchen scheint die Trainingsphase zu kurz sein. Eine tiefergehende Analyse der einzelnen Puttversuche lässt die Vermutung zu, dass die Teilnehmenden der beiden Versuchsgruppen in Abhängigkeit der Beobachtungsperspektive unterschiedliche Strategien verfolgt haben, um die Puttbewegung des Roboters zu verbessern. Die Probanden der Frontal-Gruppe scheinen die Korrekturen von der beobachteten Roboterbewegung abzuleiten, während die Probanden der Sagittal-Gruppe Korrekturen nicht von der beobachteten Roboterbewegung, sondern von der vorherigen, selbst durchgeführten Puttbewegung ableiten. Eine mögliche Begründung für diese unterschiedlichen Korrekturstrategien kann in der Qualität der in Abhängigkeit

von der Beobachtungsperspektive wahrnehmbaren räumlich-zeitlichen Informationen begründet sein. Diese stützt wiederum die Annahme, dass eine Beobachtung aus der Frontal-Perspektive Vorteile bei der Beobachtung einer Roboterputtbewegung gegenüber einer Beobachtung aus der Sagittal-Perspektive hat, auch wenn dies durch die Entwicklung der Puttleistung der beiden Versuchsgruppen nicht verifiziert wird.

Des Weiteren wurde erwartet, dass sich die Ergebnisse des Puttleistungstests von Pre- zu Post-Test der beiden Interventionsgruppen (Frontal- und Sagittal-Gruppe) im Vergleich zur Entwicklung der Kontrollgruppe stärker verbessern.
Alle Gruppen konnten ihre Puttleistung vom Pre- zum Posttest tendenziell verbessern. Den größten Leistungszuwachs zeigten die beiden Interventionsgruppen mit einer Verbesserung von 22.8 % (Sagittal-Gruppe) und 17.1 % (Frontal-Gruppe). Die Kontrollgruppe konnte die Puttleistung um 5.5 % steigern. Es lassen sich tendenzielle Unterschiede zwischen den beiden Interventionsgruppen und der Kontrollgruppe feststellen, diese werden jedoch nicht signifikant. Die Hypothese, dass die beiden Interventionsgruppen ihre Leistung im Vergleich zur Kontrollgruppe stärker steigern können, muss zurückgewiesen werden. Es wird vermutet, dass die kurze Trainingsphase von sieben Puttversuchen nicht ausreichend lang ist, um einen größeren Trainingseffekt zu erreichen. Ein weiterer Grund wird darin vermutet, dass die Puttleistungstests "frei" durch den Menschen ausgeführt wurden, während in der Trainingsphase alle Putts in Kombination mit dem Roboter absolviert wurden.

Die Ergebnisse werfen insgesamt die Frage auf, welche räumlich-zeitlichen Informationen einer Roboterputtbewegung vom Menschen wahrgenommen und eingeschätzt werden können.

5.1.2 Wahrnehmung unter vollständiger und unvollständiger Bedingung

In Anlehnung an den FLE wurde erwartet, dass der Fehler der Vorhersage der Puttleistung mit Bewegungsgeschwindigkeit ebenfalls zunimmt (Hypothese 1). Der Anstieg der Bewegungsgeschwindigkeit ist bedingt durch den gleichbleibenden Weg vom Umkehrpunkt der Ausholbewegung bis zum Treffpunkt von Schläger und Ball. Um einen größeren Impuls auf den Ball zu übertragen (= größere Puttdistanz), muss der Schläger bei gleichbleibenden Weg stärker beschleunigt werden. Daraus resultiert eine höhere Bewegungsgeschwindigkeit.
Unter der vollständigen Bedingung wurden alle Distanzen überschätzt. Der Fehler der Vorhersage der Puttleistung (*constant error*) nahm mit steigender Distanz ab. Die Entwicklung des Vorhersagefehlers widerspricht der Hypothese 1. Unter der unvollständigen Bedingung zeigte sich die Tendenz der Probanden, die Puttleistung unabhängig von der realen Distanz im Zentrum der Bewertungsskala einzuschätzen.
Auf Grund dieser Tendenz kommt es beim Vorhersagefehler (*constant error*) zu einem Vorzeichenwechsel im Übergang von niedrigen zu großen Distanzen. Eine Vorhersage der Puttleistung unter der unvollständigen Bedingung scheint nicht möglich. Einen Grund stellt die sehr kurze Dauer der visuellen Information unter dieser Bedingung dar. Unterschiede zwischen den einzelnen Distanzen können ausschließlich aus der Anschwungphase (Umkehrpunkt bis Treffpunkt von Schläger und Ball) mit einer Dauer von 0.46 bis 0.58 Sekunden abgeleitet werden. Diese Zeitspanne scheint zu kurz, um die relevanten räumlich-zeitlichen Informationen der Bewegung zu erfassen. Aufgrund der Tendenz zur Mitte der Bewertungsskala über alle Distanzen hinweg, kann die Hypothese 1 unter der unvollständigen Bedingung ebenfalls nicht gestützt werden. Die Ergebnisse der Studie 1 konnten in der Studie 2 repliziert werden.

Des Weiteren wurde erwartet, dass unter der vollständigen Bedingung die Vorhersage der Puttdistanz genauer, mit einer größeren Sicherheit und schneller im Vergleich zur unvollständigen Bedingung erfolgt (Hypothese 2). Die vorhergesagte Puttleistung unterscheidet sich signifikant zwischen der vollständigen und der unvollständigen Bedingung. Unter der vollständigen Bedingung werden alle Distanzen systematisch

überbewertet, mit steigender realer Distanz steigt auch die vorhergesagte Distanz an. Der Vorhersagefehler (*constant error*) nimmt mit steigender Distanz leicht ab. Unter der unvollständigen Bedingung ist die vorhergesagte Distanz bei steigender realer Puttdistanz annähernd konstant. Es zeigt sich über alle Distanzen eine Tendenz zur Mitte der Vorhersageskala. Auf Grund dieser Tendenz zeigt der Vorhersagefehler einen Vorzeichenwechsel im Übergang von kleinen zu großen Distanzen.
Die Einschätzung der Sicherheit der Vorhersage der Puttdistanz zeigt signifikante Unterschiede zwischen der vollständigen und der unvollständigen Bedingung. Über alle Distanzen hinweg wird die Sicherheit der Vorhersage unter der vollständigen Bedingung im Vergleich zur unvollständigen Bedingung höher bewertet. Der Unterschied beträgt im Durchschnitt 0.59. Dieses Ergebnis konnte in Studie 2 repliziert werden und bestätigt die Unsicherheit der Probanden bei der Vorhersage der Puttdistanz unter der unvollständigen Bedingung. In Bezug auf die Antwortzeit zeigen sich ebenfalls signifikante Unterschiede zwischen den beiden Bedingungen. Über alle Distanzen ist die Antwortzeit unter der vollständigen Bedingung im Vergleich zur unvollständigen Bedingung durchschnittlich 0.92 Sekunden schneller. Dieses Ergebnis konnte in Studie 2 nicht repliziert werden.
Insgesamt zeigen die Ergebnisse, dass unter der vollständigen Bedingung die Vorhersage genauer, mit einer größeren Sicherheit und schneller erfolgt als unter der unvollständigen Bedingung - Hypothese 2 kann somit angenommen werden. Die Ergebnisse belegen die Bedeutung der Bewegungsphase nach dem Treffpunkt des Balls für die Vorhersage der Puttleistung.

Darüber hinaus wurde erwartet, dass die Vorhersagen unter der vollständigen, nicht manipulierten Bedingung (d.h. sichtbarem Roboter, Schläger und Ball) genauer, sicherer und schneller sind im Vergleich zu den vollständigen, nach dem Treffpunkt von Schläger und Ball manipulierten Bedingungen, d.h. unsichtbarer Ball oder Schläger (Hypothese 3). Es zeigten sich signifikante Unterschiede zwischen den drei vollständigen Bedingungen und der unvollständigen Bedingung, dagegen wurden die Unterschiede zwischen den vollständigen Bedingungen nicht signifikant. Bei der Vorhersage der Puttgenauigkeit zeigten sich tendenzielle Vorteile der vollständigen Bedingung ohne sichtbaren Ball (F-RCH) gegenüber den anderen Bedingungen. Unterschiede der Sicherheit der Vorhersage wurden ebenfalls nur zwischen den drei vollständigen und der unvollständigen Bedingung signifikant. Die vollständige Bedingung ohne sichtbaren Roboter, Schläger und Schlägerkopf (F-B) zeigte mit Ausnahme der Distanz von 4 Metern die geringsten Antwortzeiten.
Insgesamt muss die Hypothese 3 zurückgewiesen werden, die Unterschiede in der Genauigkeit der Vorhersage, deren Sicherheit und der Antwortzeit unter der vollständigen sowie den vollständigen, manipulierten Bedingungen wurden nicht signifikant.

Die Ergebnisse der beiden vorgestellten Studien unterstreichen die Bedeutung der Puttbewegungsphase nach dem Treffpunkt von Schläger und Ball für die Beurteilung des Ergebnisses der Bewegung. Unklar bleibt die Bedeutung unterschiedlicher Kombinationen von einzelnen Elementen der Bewegung, z. B. Roboter, Schläger und Ball, die teils redundante räumlich-zeitliche Informationen liefern. Aus diesem Grund ist eine weitere Differenzierung dieser Elemente nötig.

5.1.3 Wahrnehmung unter manipulierten vollständigen Bedingungen

Aufbauend auf den bereits gewonnenen Erkenntnissen zur Bedeutung der Puttbewegungsphase nach dem Treffpunkt von Schläger und Ball, wurde die vollständige Bedingung durch Ausblenden unterschiedlicher Elemente (z. B. Roboter, Schläger, Schlägerkopf oder Ball) manipuliert.

Es wurde angenommen, dass die Vorhersage unter den Bedingungen mit sichtbarem Ball (F-RCHB, F-CHB und F-HB) im Vergleich zur Bedingung ohne sichtbaren Ball (F-RCH, F-CH und F-H) genauer sind.
Die Ergebnisse stützen diese Hypothese, insbesondere für größere Distanzen scheint eine Vorhersage der

Puttleistung ohne sichtbaren Ball unter den drei Bedingungen nicht möglich zu sein. Für große Distanzen besteht unter den Bedingungen ohne sichtbaren Ball eine Tendenz zur Mitte der Bewertungsskala, eine Vorhersage scheint nicht möglich zu sein. Die Sichtbarkeit des Balls in der Bewegungsphase nach dem Treffpunkt von Schläger und Ball hat einen großen Einfluss auf die Genauigkeit der Vorhersage der Puttleistung.

Im Unterschied zu den bisherigen Erkenntnissen werden nicht alle Distanzen unter den drei vollständigen Bedingungen überschätzt, insbesondere die nicht manipulierte vollständige Bedingung (F-RCHB) zeigt einen deutlich flacheren Anstieg der vorhergesagten Puttleistung und unterschätzt diese für große reale Puttdistanzen.
Die Kombination von Bedingungen mit unterschiedlichen sichtbaren Elementen des Roboter-Schläger-Systems sowie des Balls scheint einen negativen Einfluss auf die Genauigkeit der Vorhersage der Puttleistung unter der vollständigen Bedingung zu haben. Eine weitere Analyse der erhobenen Daten in Bezug auf die unterschiedlichen Fehlermaße (*constant error, absolute error, variable error*), die Sicherheit der Vorhersage sowie der Reaktionszeit, sollte durchgeführt werden, um ein besseres Verständnis der vorliegenden Daten zur Vorhersage der Puttleistung zu ermöglichen.

Bei der Interpretation der Ergebnisse muss das Design der Studie berücksichtigt werden. Die Gesamtpopulation wurde in drei Gruppen eingeteilt. Jeder Gruppe wurden lediglich vier der insgesamt sechs Bedingungen gezeigt. Die den drei Gruppen zugewiesenen Kombinationen der vier Bedingungen stellten die insgesamt drei möglichen Kombinationen dar. Ein direkter Vergleich der Ergebnisse der drei Gruppen ist auf Grund des beschriebenen Designs nicht möglich. In zukünftigen Untersuchungen sollte dieses Problem berücksichtigt werden und allen Probanden alle Bedingungen gezeigt werden. Dies führt allerdings zu einer verlängerten Untersuchungszeit, da insgesamt 72 Videosequenzen anstatt der bisher 48 bewertet werden müssen.

5.1.4 Mensch-Mensch Interaktion

Ziel der explorativen Studie war die Prüfung eines möglichen dyadischen Lernprotokolls zum Erlernen der Golfputtbewegung. Zum Einen sollte geprüft werden, ob die von Granados (2010) sowie Poolton et al. (2006) vorgeschlagene Versuchsanordnung für Mensch-Mensch-Dyaden geeignet ist und welche Komponenten der Mensch-Mensch-Interaktion auf Mensch-Roboter-Interaktionen transferierbar sind.
Die Puttleistung der Probanden konnte signifikant zwischen den einzelnen Übungsblöcken gesteigert werden. Dies zeigt, dass die Mensch-Mensch-Dyaden durch die Kombination von Ausführung, Beobachtung und Dialogen einen gemeinsamen Bewegungslernprozess bewältigen können. Zu hinterfragen ist an dieser Stelle, ob sich die Effekte unter einem vergleichbaren Protokoll ohne die Dialoge, nur auf Basis von Eigenrealisierung und Beobachtung des Partners, oder unter einem Protokoll mit isolierter Durchführung einer einzelnen Person nicht ebenfalls eingestellt hätten. Es konnte nicht geklärt werden, welchen Einfluss die einzelnen Versuchselemente (Eigenrealisierung, Beobachtung und Dialoge) auf die Entwicklung der Puttleistung haben. Dies sollte in zukünftigen Studien tiefergehend geprüft werden. Ein mögliches Studiendesign könnte auf dem hier vorgestellten Design aufbauen und mit mehreren Versuchs- und Kontrollgruppen agieren. Insbesondere sollten die folgenden Kombinationen untersucht werden:

1) Eigenrealisierung, Beobachtung und Dialoge
2) Eigenrealisierung und Beobachtung
3) Eigenrealisierung und Dialog

4) Kontrollgruppe (isolierte Durchführung der Puttversuche ohne Dialoge)

Ein weiterer Schwerpunkt der Studie war die Identifizierung von Themen innerhalb der Dialoge, die auf Mensch-Roboter-Interaktionen transferiert werden können. Insgesamt konnten 867 einzelne Aussagen in den 60 Dialogen kategorisiert werden. Diese Aussagen wurden den vier Hauptkategorien Konkret - bewegungsbezogen, Allgemein - bewegungsbezogen, Meta-Aussagen und Regelwissen zugeordnet. Am häufigsten wurden Themen der Kategorie konkret - Bewegungsbezogen (434 Nennungen) genannt, gefolgt von den Kategorien Meta-Aussagen (285), Allgemein - bewegungsbezogen (115) und Regelwissen (33). Kategorieübergreifend wurden die Themen Länge, Distanz, Kraft, Schwung (113 Nennungen), Ausgangsstellung (91), Partner (73), Bewegungskontrolle (60) sowie Pendel/Schwingen (47) genannt.
Die benannten Themen können teilweise auf die Mensch-Roboter-Interaktion übertragen werden bzw. lassen sich auch durch ein technisches System als Information für den Roboter erfassen. Dies sind insbesondere Informationen über die Puttleistung (Länge, Distanz, Kraft und Schwung), die sich aus der finalen Position des Ball ableiten lassen. Eine Erfassung kann kamerabasiert automatisiert werden. Andere Themen spiegeln sich in der unterschiedlichen Bauweise von Mensch und Roboter wieder, z. B. die Thematisierung von Pendel/Schwingen. Der Roboter besitzt den Vorteil, ein Pendel darzustellen, dies kann vom Menschen beobachtet und ggf. in die eigene Bewegungsvorstellung integriert werden.

In weiteren Analysen muss sehr detailliert geprüft werden, welche Informationen von einem technischen System in ausreichender Qualität und Geschwindigkeit erfasst werden und dem Menschen kommuniziert werden können. In diesem Zusammenhang muss auch geklärt werden, auf welche Weise eine Kommunikation zwischen Mensch und Roboter stattfinden kann.

5.1.5 Iteratives Roboter-Feedback

Es wurde angenommen, dass eine an die Reaktion des Menschen angepasste adaptive Korrekturstrategie gegenüber einer konstanten Korrekturstrategie von Vorteil für das Erlernen einer Bewegungstrajektorie durch den Menschen ist. Diese Annahme wird durch die Ergebnisse der Studie nicht gestützt.

Problematisch erscheint die Berechnung der Parameter α und β. Diese wurden nach jeder Iteration neu berechnet und zeigen aus diesem Grund starke Schwankungen. Daraus resultieren auch starke Unterschiede der Intensität des haptischen Feedbacks durch den Roboter. Diese Schwankungen konnten von den Probanden anscheinend nicht korrekt bewertet werden und führten nicht zum gewünschten Lernerfolg.

Die Ergebnisse der Studie müssen im Hinblick auf das Design der Studie kritisch betracht werden. Zum einen wurden mit insgesamt vier Probanden, aufgeteilt auf zwei Versuchsgruppen, nur sehr wenige Probanden untersucht. Zum anderen fehlte eine Kontrollgruppe.

Insgesamt bietet der Ansatz eine gute Basis für zukünftige Studien. Die Berechnung der Parameter α und β sollte in weiteren Untersuchungen nicht nach jeder Iteration erfolgen, um dem Roboter ein gleichbleibendes Feedback für den lernenden Menschen zu ermöglichen. Es gilt optimale Zeitspannen bzw. Wiederholungen für die Anpassung der Intensität des haptischen Roboterfeedbacks zu ermitteln. Das Design der Studie sollte durch eine zusätzliche Kontrollgruppe erweitert und die Anzahl der Probanden erhöht werden.

5.2 Limitationen dieser Arbeit

Im folgenden Abschnitt werden die Grenzen dieser Arbeit beschrieben. Diese Limitationen wurden z. T. in den Publikationen aufgegriffen und werden im folgenden Abschnitt zusammengefasst und ergänzt.

5.2.1 Roboter-System

Das in den einzelnen Kapiteln beschriebene BioRob-System hat Vor- und Nachteile. Vorteile bieten die sehr leichte und dem menschlichen Arm nachempfundene Konstruktion, die Installation der Aktuatoren in der Basis sowie die Verbindung der Aktuatoren mit den Segmenten des Roboters durch elastische Seil-Feder-Kombinationen. Auf Grund dieser speziellen Bauweise werden bei den Bewegungen des Roboters nur sehr kleine Kräfte erzeugt und eine direkte Interaktion mit dem Menschen ohne den Einsatz eines Kollisionswarnsystems ermöglicht.

Teilweise haben sich die beschriebenen Vorteile auch als Nachteile des Systems erwiesen. Durch die Leichtbauweise des Roboters musste für die Experimente mit dem Golfputter der Endeffektor entfernt werden. Dieser konnte den durch den langen Hebelarm des Golfputters erzeugten Kräften nicht standhalten. Als Folge hat der Roboter einen Freiheitsgrad eingebüßt. Supination und Pronation des letzten Segments des Roboters (vergleichbar mit dem Unterarm) konnten nicht mehr realisiert werden. Eine Anpassung der Ausrichtung der Schlägerfläche und somit der Puttrichtung konnte durch den Roboter nicht mehr selbstständig durchgeführt werden. Durch diese Limitation der Freiheitsgrade konnten die Untersuchungen ausschließlich auf die Puttlänge und nicht auf die Puttrichtung bezogen werden.

Ein weiters Problem ergab sich aus der Ansteuerung der einzelnen Robotersegmente über elastische Seil-Feder-Systeme. Durch dieses System konnte der Roboter Trajektorien nicht exakt reproduzieren.
Durch die beschriebenen großen Kräfte, die durch den Schläger erzeugt wurden, sind zusätzliche Schwingungen im Gesamtsystem entstanden, die die exakte Kontrolle der Roboterbewegung verlangsamt und erschwert haben.

Für die weitere Forschung ist es nötig, entweder ein passendes Robotersystem auszuwählen, das die durch den Schläger erzeugten Kräfte verkraften kann sowie Supination und Pronation ermöglicht oder eine andere sportliche Bewegung, z. B. Tischtennis, zu nutzen.

5.2.2 Berücksichtigung der Vorerfahrung

Der Einfluss der Vorerfahrung auf die Genauigkeit der Vorhersage der Puttleistung wurde bisher nicht berücksichtigt. In allen Untersuchungen wurden die Probanden nach ihrer Vorerfahrung in den vier Bereichen Golf, Feldhockey und ähnliche; Rückschlagspiele; Ballspiele und Computerspiele befragt und gaben diese in Jahren der Ausübung sowie der durchschnittlichen Ausübungszeit pro Woche an. Im Rahmen der Auswertung der Versuchsdaten wurden diese Informationen bisher nicht berücksichtigt. Es ist vorstellbar, dass z. B. die Vorerfahrung in Computerspielen einen positiven Einfluss auf die Wahrnehmung der präsentierten Videoszenen haben kann. Sportliche Vorerfahrung, insbesondere im Bereich der Rückschlagspiele und der golfähnlichen Sportarten, kann einen positiven Einfluss auf die Erfassung der räumlich-zeitlichen Informationen haben.

Eine tiefergehende Analyse der Versuchsdaten unter Berücksichtigung der Vorerfahrung sollte durchgeführt werden. Die Ergebnisse können Aufschluss auf die Zusammensetzung zukünftiger Versuchsgruppen ergeben.

5.2.3 Focus of attention

Bisher konnte lediglich das Ergebnis der Wahrnehmungsleistung in Form einer Vorhersage von Puttdistanzen untersucht werden. Unbeachtet blieb die Blickrichtung bzw. der Fokus der Aufmerksamkeit der Probanden während der Präsentation der einzelnen Videosequenzen. Bisher ist ungeklärt, welches Eye-Tracking-Verfahren im Rahmen des vorgestellten Untersuchungsdesigns eingesetzt werden könnte. Zusätzliche Informationen über die Blickrichtung können bisherige Ergebnisse bestätigen und Blickstrategien der Probanden aufzeigen.

5.3 Ausblick

Zukünftige Arbeiten sollten zunächst die bisherigen Studien erweitern. Im Bereich der unidirektionalen Interaktion von zweier Menschen ist aufgrund des in Kapitel 2.3 vorgestellten Untersuchungsdesigns bisher offen geblieben, auf welchen Faktoren die Leistungsverbesserung der Teilnehmenden basiert. Das Studiendesign sollte entsprechend um zusätzliche Versuchsgruppen erweitert werden. Neben der Gruppe mit den drei Elementen (Eigenrealisierung, Beobachtung und Dialog) sollten zusätzliche Gruppen die folgenden Kombinationen abdecken:

1) Eigenrealisierung und Dialog;
2) Eigenrealisierung und Beobachtung;
3) Eigenrealisierung durch Proband A, Beobachtung durch Proband B und Dialog.

Zusätzlich sollte eine Kontrollgruppe eingesetzt werden, deren Probanden lediglich das Element der Eigenrealisierung abdecken. Durch diese Kontrollgruppe kann ausgeschlossen werden, dass es sich bei der Leistungsverbesserung der einzelnen Gruppen um einen Effekt ausschließlich auf der Basis der Eigenrealisierung handelt. Um eine Vergleichbarkeit zukünftiger Untersuchungen mit den Ergebnissen der Studie von Granados (2010) zu ermöglichen, sollte neben der radialen Distanz zum Zielpunkt auch ein Bewertungsraster für die Beurteilung der Leistung herangezogen werden. Durch diese Erweiterung des Studiendesigns können zusätzliche Erkenntnisse über die Bedeutung von Eigenrealisierung, Beobachtung und Dialogen im Rahmen eines dyadischen Bewegungslernprozesses gewonnen werden. Diese können dann auf Roboter-Mensch-Dyaden übertragen werden.

Im Bereich der visuellen Wahrnehmung von Roboterbewegungen durch den Menschen gilt es, die in der Diskussion skizzierten offenen Fragestellungen zu bearbeiten.
Die in Artikel III vorgestellte Studie sollte in ihrem Design angepasst werden, um eine direkte Vergleichbarkeit zwischen den einzelnen Bedingungen zu ermöglichen. Zusätzlich sollte ein Eye-Tracking-System eingesetzt werden, um die Blickrichtung der Probanden zu erfassen. Basierend auf diesen Daten kann geklärt werden, auf welche Elemente der Roboterputtbewegung die Probanden ihren Beobachtungsfokus legen.
Der Einfluss der Beobachtungsperspektive wurde in der vorgestellten Studie mit einer Trainingsphase verbunden. An dieser Stelle sollte zunächst untersucht werden, welche Informationen aus den einzelnen Perspektiven wahrgenommen werden können. Das in den späteren Studien vorgestellte Design unter Nutzung von Videosequenzen scheint ein möglicher Ansatz zu sein, diese Problemstellung zu bearbeiten. Den Probanden könnten vollständige Roboterputtbewegungen aus unterschiedlichen Perspektiven präsentiert werden, mit der Aufgabe, die jeweilige Puttdistanz vorherzusagen. Durch die Verwendung von standardisierten Videosequenzen über unterschiedliche Distanzen können die Probleme in der Ansteuerung des

Roboters umgangen werden und es ist sichergestellt, dass die Puttbewegungen über eine bestimmte Distanz exakt repliziert werden können. Der Einfluss einer Trainingsphase kann so verhindert werden. Zusätzlich sollten die Blickbewegung der Probanden mit einem Eye-Tracking-System erfasst werden. Basierend auf der Blickrichtung kann erfasst werden, auf welche Elemente der Roboterputtbewegung die Probanden ihren Fokus legen und es kann geprüft werden, ob es in diesem Zusammenhang zu unterschiedlichen Blickstrategien in Abhängigkeit der Blickrichtung kommt. Die Erkenntnisse über die Bedeutung der Beobachtungsperspektive können in den zukünftigen Ansätzen eines gemeinsamen Bewegungslernprozesses von Mensch und Roboter integriert werden.

Neben den bisherigen Ansätzen zur visuellen Wahrnehmung sollten zukünftige Studien um zusätzliche Informationen in Form eines haptischen Feedbacks erweitert werden. Eine prototypische Untersuchung könnte dem folgenden Studiendesign unterliegen. Die Probanden werden insgesamt vier Versuchsgruppen zugeordnet:

1) Haptische Führung durch den Roboter
2) Visuelle Führung durch den Roboter
3) Kombination von haptischer und visueller Führung durch den Roboter
4) Kontrollgruppe ohne Führung durch den Roboter

Unter haptischer Führung werden die Probanden durch den Roboter entlang einer vorprogrammierten Trajektorie geführt. Die Sicht wird z. B. durch eine Brille verdeckt. Unter der visuellen Bedingung beobachten die Probanden den Roboter bei der Ausführung einer Puttbewegung aus einer möglichst optimalen Beobachtungsperspektive (siehe Beschreibung im vorherigen Abschnitt). Unter der Kombination von haptischer und visueller Führung durch den Roboter werden die Probanden alternierend unter den beiden Bedingungen geführt.
Es wird erwartet, dass eine Kombination von haptischer und visueller Führung im Vergleich zu einer isolierten haptischen bzw. visuellen Führung einen effizienteren Bewegungslernprozess ermöglicht.
Unter den verschiedenen Führungsbedingungen sollte ebenfalls der Einfluss einer Reduktion der Führung durch den Roboter im Verlauf des Bewegungslernprozesses untersucht werden. Wie lang ist eine starke Führung durch den Roboter nötig und wie kann ein entsprechendes Ausschleichen erreicht werden.

Unter Berücksichtigung der zuvor beschriebenen Untersuchung zur optimalen Führung durch den Roboter sowie der Erkenntnisse zum iterrativen Roboter-Feedback (Artikel I) sollte untersucht werden, ob ein konstantes oder an die Leistung der Probanden angepasstes Roboter-Feeback zu einem effizienteren Bewegungslernprozess beitragen kann. In Abhängigkeit der Ergebnisse kann das Design durch den Einsatz von Bewegungsvariationen erweitert werden. Dies können Variationen ohne oder mit Einfluss auf die Puttlänge sein. So führt z. B. eine Veränderung des Gelenkwinkels des Unterarms in der Anschwungbewegung nicht zu einem veränderten Impuls auf den Ball. Unter der optimalen Führungsstrategie können Versuchsgruppen mit aufgabenrelevanten, aufgabenirrelevanten und ohne jegliche Variation trainiert werden. Basierend auf den bisherigen Erkenntnissen kann davon ausgegangen werden, dass eine aufgabenrelevante Variation der Führung zu einem verbesserten Lernerfolg führt (He et al., 2016).

Neben den beschriebenen Untersuchungen mit dem Fokus auf den Faktor Mensch müssen auch weitere Erkenntnisse darüber gewonnen werden, wie ein Roboter Bewegungen von einem Mensch erlernen kann. Letztlich müssen die Erkenntnisse dieser beiden unidrektionalen Interaktions-Modelle in ein bidirektionales Bewegunslernmodell von Mensch-Roboter-Dyaden überführt werden. Einen Schwerpunkt wird insbesondere die Kommunikation zwischen Mensch und Roboter darstellen und somit die Entwicklung geeigneter Informationsschnittstellen.

Auch in Zukunft werden die direkten Interaktionen zwischen Mensch und Roboter zunehmen. Eine wichtige Aufgabe der Wissenschaft sollte es sein, die dahinter liegenden Prozesse der beiden Teilsysteme zu verstehen und optimal aneinander anzupassen. Bei dieser technologischen Entwicklung darf der Mensch allerdings nicht zu einem Subsystem eines Roboters degradiert werden. Die Technologie, in diesem Fall lernende Robotersysteme, sollten im Rahmen einer Interaktion mit einem Menschen immer diesen in den Fokus der Betrachtung stellen. Nicht der Mensch sollte sich der Technologie anpassen, sondern die Technologie dem Menschen.

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Anhang

Zusätzliches Material

Artikel II: Perception and prediction of robot movements under different visual/viewing conditions

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S1-File

Power calculation for Study 1

Post hoc: Compute achieved power - hypothesis 2 - predicted distance

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 1.3748358
	α err prob	= 0.05
	Total sample size	= 20
	Number of groups	= 2
	Number of measurements	= 6
	Corr among rep measures	= 0.672
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 691.5269
	Critical F	= 2.3156892
	Numerator df	= 5.0000000
	Denominator df	= 90.0000000
	Power $(1 - \beta$ err prob)	= 1.0000000

Post hoc: Compute achieved power - hypothesis 2 - constant error

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 1.3748358
	α err prob	= 0.05
	Total sample size	= 20
	Number of groups	= 2
	Number of measurements	= 6
	Corr among rep measures	= 0.672
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 691.5269
	Critical F	= 2.3156892
	Numerator df	= 5.0000000
	Denominator df	= 90.0000000
	Power $(1 - \beta$ err prob)	= 1.0000000

Post hoc: Compute achieved power - hypothesis 2 - confidence

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 1.4746536

	α err prob	= 0.05
	Total sample size	= 20
	Number of groups	= 2
	Number of measurements	= 6
	Corr among rep measures	= 0.546
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 574.785
	Critical F	= 2.3156892
	Numerator df	= 5.0000000
	Denominator df	= 90.0000000
	Power $(1 - \beta$ err prob)	= 1.0000000

Post hoc: Compute achieved power - hypothesis 2 - response time

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 1.6236883
	α err prob	= 0.05
	Total sample size	= 20
	Number of groups	= 2
	Number of measurements	= 6
	Corr among rep measures	= 0.231
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 411.3962
	Critical F	= 2.3156892
	Numerator df	= 5.0000000
	Denominator df	= 90.0000000
	Power $(1 - \beta$ err prob)	= 1.0000000

S2-File

Power calculation for Study 2

A priori: Compute required sample size - hypothesis 2

F tests - ANOVA: Repeated measures, within factors		
Analysis:	A priori: Compute required sample sizer	
Input:	Effect size f	= 1.3748358
	α err prob	= 0.05
	Power ($1 - \beta$ err prob)	= 0.80
	Number of groups	= 2
	Number of measurements	= 3
	Corr among rep measures	= 0.672
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 69.1526882
	Critical F	= 6.9442719
	Numerator df	= 2.0000000
	Denominator df	= 4.0000000
	Total sample size	= 4
	Actual power	= 0.9975382

A priori: Compute required sample size - hypothesis 3

F tests - ANOVA: Repeated measures, within factors		
Analysis:	A priori: Compute required sample sizer	
Input:	Effect size f	= 0.5
	α err prob	= 0.05
	Power ($1 - \beta$ err prob)	= 0.80
	Number of groups	= 4
	Number of measurements	= 3
	Corr among rep measures	= 0.5
	Nonsphericity correction ϵ	= 1
Output:	Noncentrality parameter λ	= 18.0000000
	Critical F	= 3.6337235
	Numerator df	= 2.0000000
	Denominator df	= 16.0000000
	Total sample size	= 12
	Actual power	= 0.9408513

Post hoc: Compute achieved power - hypothesis 2 - predicted distance

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.8181987
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 4
	Number of measurements	= 3
	Corr among rep measures	= 0.250
	Nonsphericity correction ϵ	= 0.639
Output:	Noncentrality parameter λ	= 32.5111267
	Critical F	= 4.0467918
	Numerator df	= 1.2780000
	Denominator df	= 19.1700000
	Power $(1 - \beta$ err prob)	= 0.9994625

Post hoc: Compute achieved power - hypothesis 2 - constant error

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.8181987
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 4
	Number of measurements	= 3
	Corr among rep measures	= 0.250
	Nonsphericity correction ϵ	= 0.639
Output:	Noncentrality parameter λ	= 32.5111267
	Critical F	= 4.0467918
	Numerator df	= 1.2780000
	Denominator df	= 19.1700000
	Power $(1 - \beta$ err prob)	= 0.9994625

Post hoc: Compute achieved power - hypothesis 2 - confidence

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.7762500
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 4
	Number of measurements	= 3
	Corr among rep measures	= 0.438
	Nonsphericity correction ϵ	= 0.685
Output:	Noncentrality parameter λ	= 41.8631919
	Critical F	= 3.9193832
	Numerator df	= 1.3700000
	Denominator df	= 20.5500000
	Power $(1 - \beta$ err prob)	= 0.9999625

Post hoc: Compute achieved power - hypothesis 2 - response time

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.2389193
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 4
	Number of measurements	= 3
	Corr among rep measures	= 0.087
	Nonsphericity correction ϵ	= 0.810
Output:	Noncentrality parameter λ	= 2.8866329
	Critical F	= 3.6341113
	Numerator df	= 1.6200000
	Denominator df	= 24.3000000
	Power $(1 - \beta$ err prob)	= 0.3056498

Post hoc: Compute achieved power - hypothesis 3 - predicted distance

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.4233737
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 3
	Number of measurements	= 3
	Corr among rep measures	= 0.250
	Nonsphericity correction ϵ	= 0.702
Output:	Noncentrality parameter λ	= 9.5630947
	Critical F	= 3.8434118
	Numerator df	= 1.4040000
	Denominator df	= 22.4640000
	Power $(1-\beta$ err prob)	= 0.7951375

Post hoc: Compute achieved power - hypothesis 3 - constant error

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.4233737
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 3
	Number of measurements	= 3
	Corr among rep measures	= 0.250
	Nonsphericity correction ϵ	= 0.702
Output:	Noncentrality parameter λ	= 9.5630947
	Critical F	= 3.8434118
	Numerator df	= 1.4040000
	Denominator df	= 22.4640000
	Power $(1-\beta$ err prob)	= 0.7951375

Post hoc: Compute achieved power - hypothesis 3 - confidence

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.4701077
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 3
	Number of measurements	= 3
	Corr among rep measures	= 0.438
	Nonsphericity correction ϵ	= 0.859
Output:	Noncentrality parameter λ	= 19.2542423
	Critical F	= 3.5156504
	Numerator df	= 1.7180000
	Denominator df	= 27.4880000
	Power $(1 - \beta$ err prob)	= 0.9746109

Post hoc: Compute achieved power - hypothesis 3 - response time

F tests - ANOVA: Repeated measures, within factors

Analysis:	Post hoc: Compute achieved power	
Input:	Effect size f	= 0.2526456
	α err prob	= 0.05
	Total sample size	= 19
	Number of groups	= 3
	Number of measurements	= 3
	Corr among rep measures	= 0.087
	Nonsphericity correction ϵ	= 0.888
Output:	Noncentrality parameter λ	= 3.5386737
	Critical F	= 3.4655441
	Numerator df	= 1.7760000
	Denominator df	= 28.4160000
	Power $(1 - \beta$ err prob)	= 0.3565220

S1-Table

Detailed results of the subgroup analysis

Tabelle 5.1: Results of the two-factor ANOVA with repeated measures (6 distances x 2 vision conditions) for the predicted putt length for the two subgroups for study 1. Corrected by Greenhouse-Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	1.000	9.000	13.775	.005	.605
	Distance	2.176	19.582	20.106	<.001	.691
	Vision condition x distance	2.904	26.135	4.095	<.001	.703
Golf experience	Vision condition	1.000	8.000	17.505	.003	.686
	Distance	1.998	15.985	24.987	<.001	.757
	Vision condition x distance	3.006	24.044	17.071	<.001	.681

Tabelle 5.2: Results of the two-factor ANOVA with repeated measures (6 distances x 2 vision conditions) for the constant error of predicted putt length for the two subgroups for study 1. Corrected by Greenhouse- Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	1.000	9.000	13.775	.005	.605
	Distance	2.176	19.582	18.309	<.001	.670
	Vision condition x distance	2.904	26.135	21.349	<.001	.703
Golf experience	Vision condition	1.000	8.000	17.505	.003	.686
	Distance	1.998	15.985	24.987	<.001	.754
	Vision condition x distance	3.006	24.044	17.071	<.001	.681

Tabelle 5.3: Results of the two-factor ANOVA with repeated measures (6 distances x 2 vision conditions) for the confidence of prediction for the two subgroups for study 1. Corrected by Greenhouse-Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	1.000	9.000	36.810	<.001	.804
	Distance	3.182	28.634	.969	.425	.097
	Vision condition x distance	3.064	27.570	1.328	.286	.129
Golf experience	Vision condition	1.000	9.000	12.100	.007	.573
	Distance	2.545	22.906	.661	.561	.068
	Vision condition x distance	2.580	23.218	1.022	<.392	.102

Tabelle 5.4: Results of the two-factor ANOVA with repeated measures (3 distances x 4 vision conditions) for the predicted putt length for the two subgroups for study 2. Corrected by Greenhouse-Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	1.917	34.499	12.041	<.001	.401
	Distance	1.588	28.580	62.148	<.001	.775
	Vision condition x distance	4.560	82.078	4.247	.002	.191
Golf experience	Vision condition	2.061	14.430	3.994	.041	.363
	Distance	1.317	10.510	35.931	<.001	.837
	Vision condition x distance	2.761	19.327	1.986	.153	.221

Tabelle 5.5: Results of the two-factor ANOVA with repeated measures (3 distances x 4 vision conditions) for the constant error of predicted putt length for the two subgroups for study 2. Corrected by Greenhouse- Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	1.917	34.499	12.041	<.001	.401
	Distance	1.588	28.580	71.997	<.001	.800
	Vision condition x distance	4.560	82.078	4.247	.002	.191
Golf experience	Vision condition	2.061	14.430	3.994	.041	.363
	Distance	1.317	9.217	44.394	<.001	.864
	Vision condition x distance	2.761	19.327	1.986	.153	.221

Tabelle 5.6: Results of the two-factor ANOVA with repeated measures (3 distances x 4 vision conditions) for the confidence of prediction for the two subgroups for study 2. Corrected by Greenhouse-Geisser ϵ.

Group	Factor	df1	df2	F	p	η_p^2
No golf experience	Vision condition	2.054	36.971	10.868	<.001	.376
	Distance	1.452	26.149	1.062	.340	.056
	Vision condition x distance	3.642	65.551	1.441	.234	.074
Golf experience	Vision condition	2.424	16.968	6.772	.005	.492
	Distance	1.410	9.870	.831	.424	.106
	Vision condition x distance	3.043	21.298	.860	.478	.109

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