MobyDick_an interactive multi-swimmer exergame

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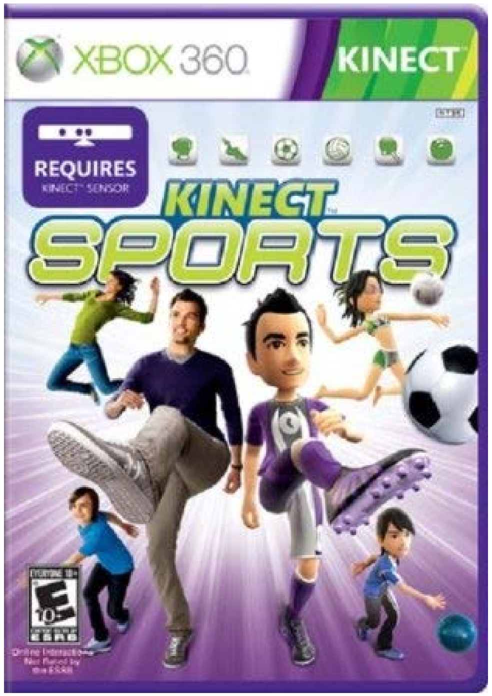
Presented by Lihua Ren

Gamifying exercise activities

- High dropout rates of fitness activities→Research on gamifying exercise activities
- Leading gaming consoles:
  - Wii Fit, Kinect Sports



Existing work

- Previous work:
  - Focusing on ground-based exercise activities
- Recent work:
  - Various water activities:
    - Games4Health workshop
    - Dungeons and Swimmers
      - Single-player game
      - Swimmer strokes are used as input for interacting with virtual objects.

Goal of this study

- Goal:
  - Transforming normal swimming activity into an interactive multi-player game.

- The interactive multi-player game:
  - A group of swimmers coordinate themselves in order to achieve the common goal of hunting a monster

Challenges

- Lack of literature on comparative performance analyses in aquatic environments.

- No information about Real-time stroke classification and the impact of skill differences on classification accuracy.

- The design of multi-player interaction is highly limited in aquatic environments.
  - Limited visual communication
  - Inability of spoken communication
  - Reduced sensitivity of auditory communication

Outline

- Motivation
- Networking performance analysis (in aquatic environment)
- Swimming stroke recognition
  - Stroke type classification
  - Stroke timing detection
- MobyDick (game design)
- Evaluation
- Discussion

Measure what?

- Performance of different networking technologies when smartphone is under water.
  - WiFi, 3G and LTE
  - Received signal strength (RSS), round trip time (RTT), packet loss rate (PLR)
  - Connection-recovering time

- Different swimming stroke -> significant difference in networking performance?

Measurement

- Waterproof Smartphone:
  - Casio G'zOne Commando LTE
  - Samsung Galaxy S4 Active
- Server: laptop connected to a wired network
- Four protocols for WiFi:
  - 802.11g (2.4 GHz) (Casio G'zOne Commando)
  - 802.11n (2.4 GHz) (Casio G'zOne Commando)
  - 802.11a/n (5 GHz) (Galaxy S4 Active)
  - 802.11ac (5 GHz) (Galaxy S4 Active)
- Two cellular operators for 3G and LTE:
  - LG U+ (Casio G'zOne Commando)
  - KT Olleh (Galaxy S4 Active)
- Environment:
  - In-lab testbed & a field trial in a real swimming pool
  - Different depth in water

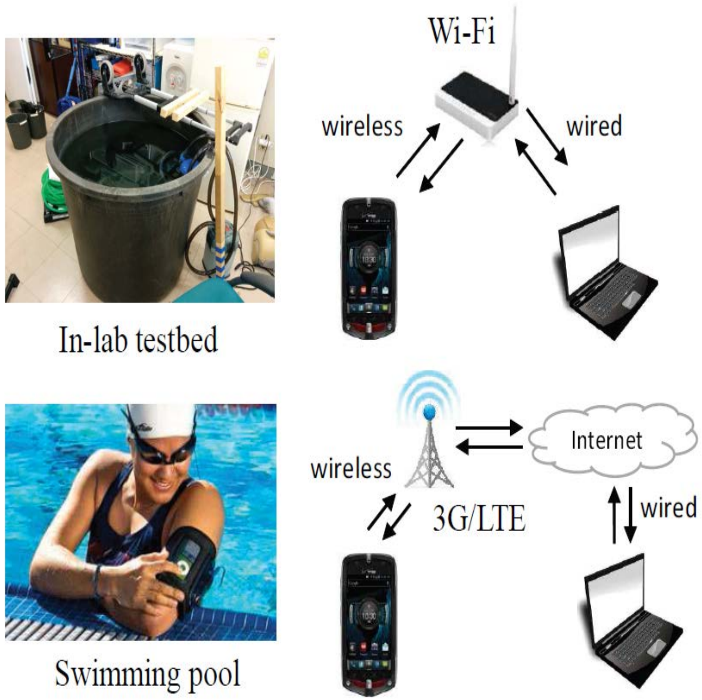
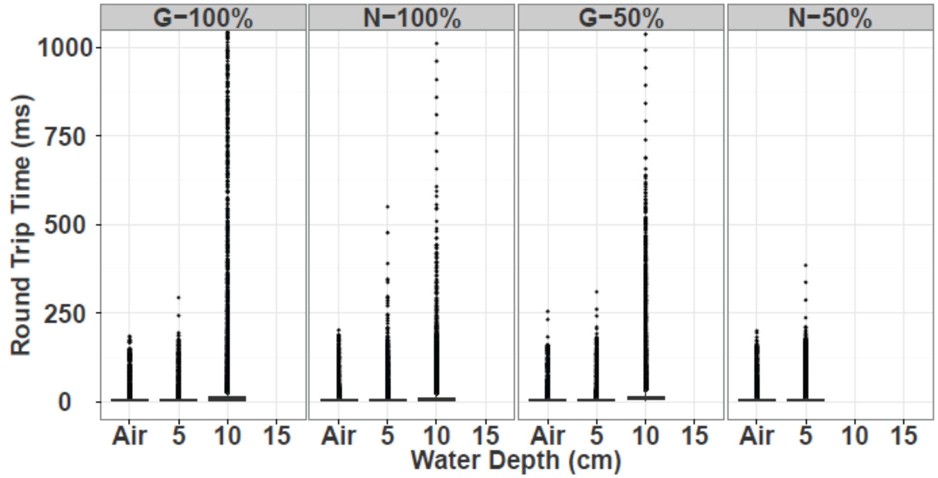
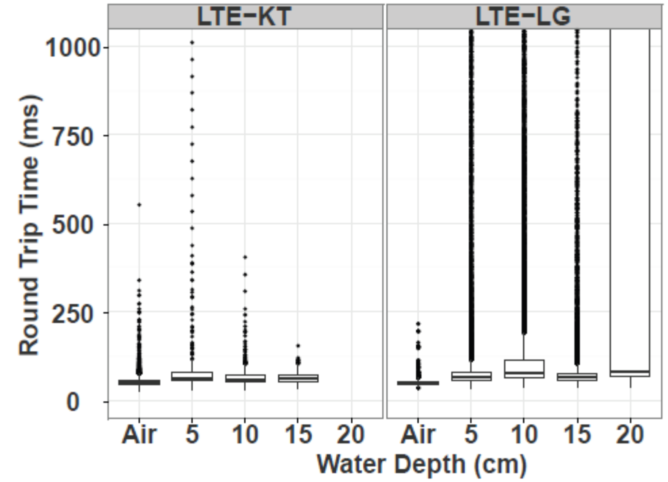


Figure 1: Measurement configuration

Measurement Results - RTT



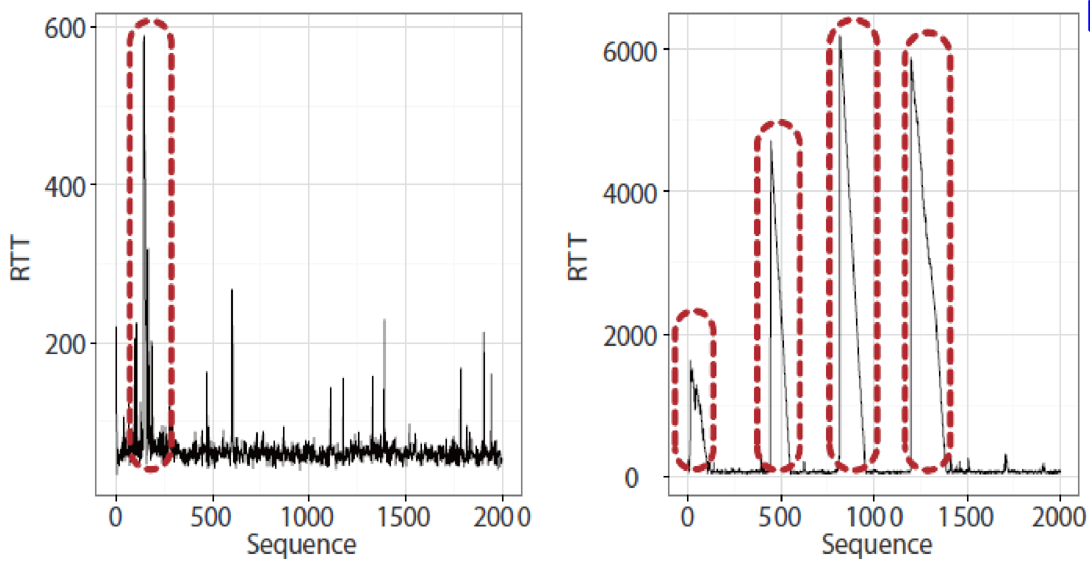
(a) RTT: 802.11g/n at 2.4Ghz; 100%/50% AP TX power



(b) RTT: LTE (KT and LG U+)

- WiFi
  - Water depth = 5 cm: not affected
  - Water depth = 10 cm: notable performance degradation
  - Water depth = 15 cm: connectivity was completely lost
- LTE
  - KT had consistently lower RTT values than LG U+

Measurement Results - RTT (continue)



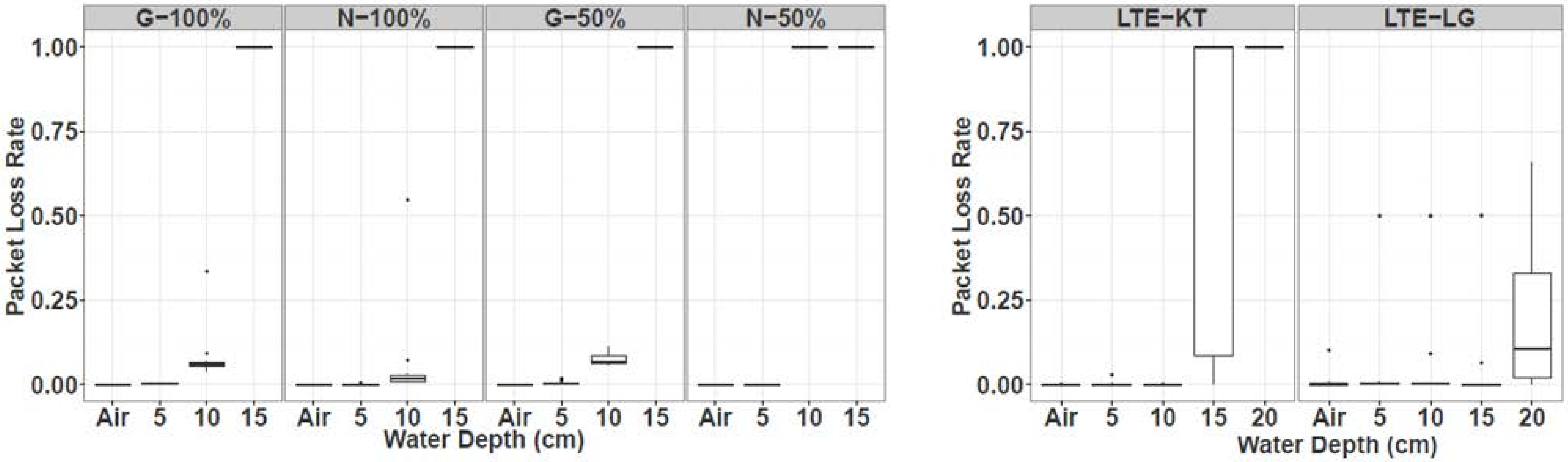
(a) Water depth of 5 cm (b) Water depth of 15 cm

Figure 5: RTT traces of LTE (LG U+) at two different water levels

- LTE (LG U+) : sudden spikes
  - After sudden spikes, RTT gradually decreased over time.
  - Spikes were followed by a bulk packet loss.

When channel condition becomes very poor, the number of retransmitted packets may reach their maximum transmission limits and eventually they are dropped, leading to bulk packet loss.

Measurement Results - PLR

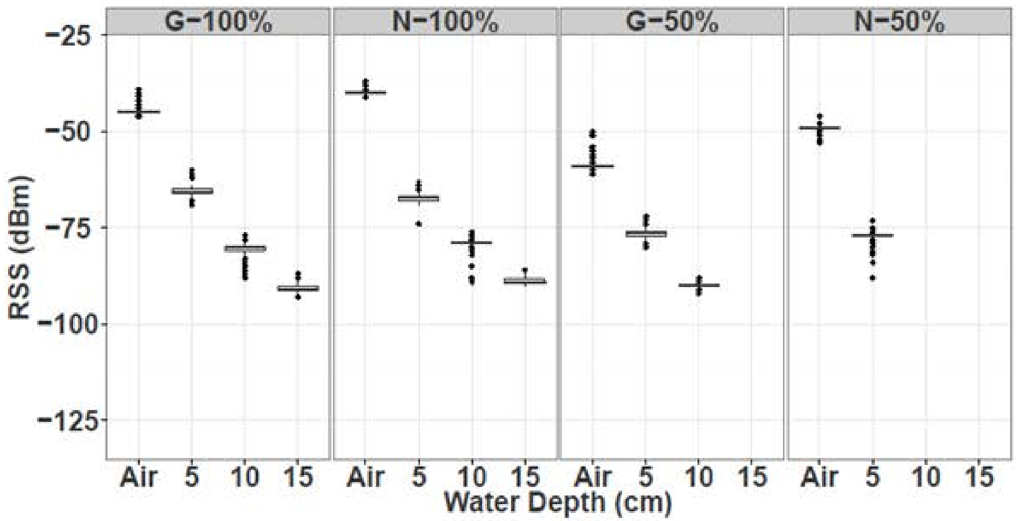


(a) PLR: 802.11g/n at 2.4Ghz; 100%/50% AP TX power

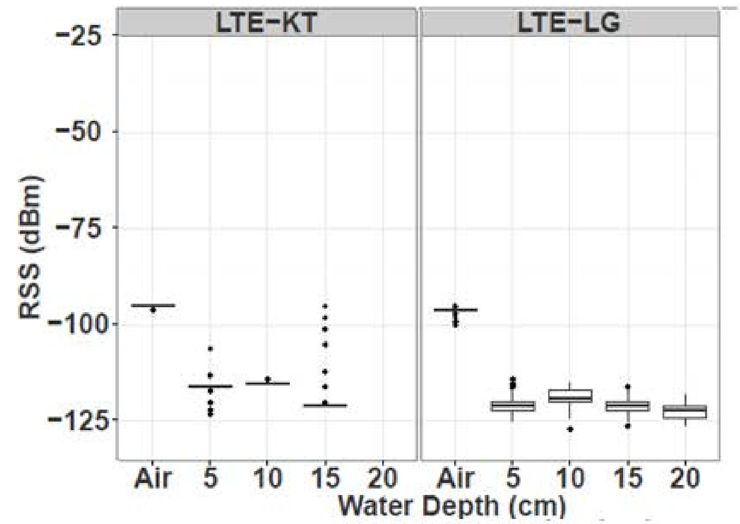
(b) PLR: LTE (KT and LG U+)

- WiFi
  - Water depth = 5 cm: almost no packet loss
  - Water depth = 10 cm: notable performance degradation
  - Water depth = 15 cm: connectivity was completely lost
- LTE
  - Water depth = 5 cm KT: no packet loss; LG : 5% packet loss
  - Water depth = 10 cm KT: no packet loss; LG : 5% packet loss
  - Water depth = 15 cm KT: 63% packet loss; LG : 50% packet loss
  - Water depth = 20 cm KT: 100% packet loss; LG : 66% packet loss

Measurement Results - RSS



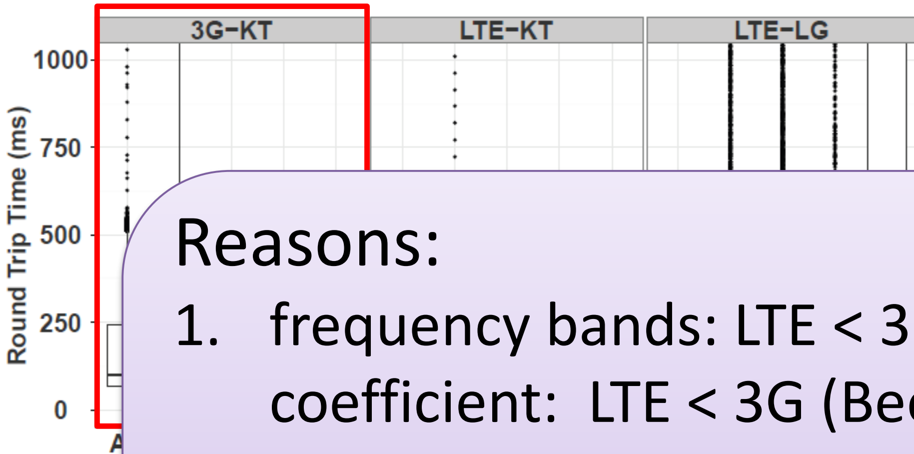
(a) RSS: 802.11g/n at 2.4Ghz; 100%/50% AP TX power

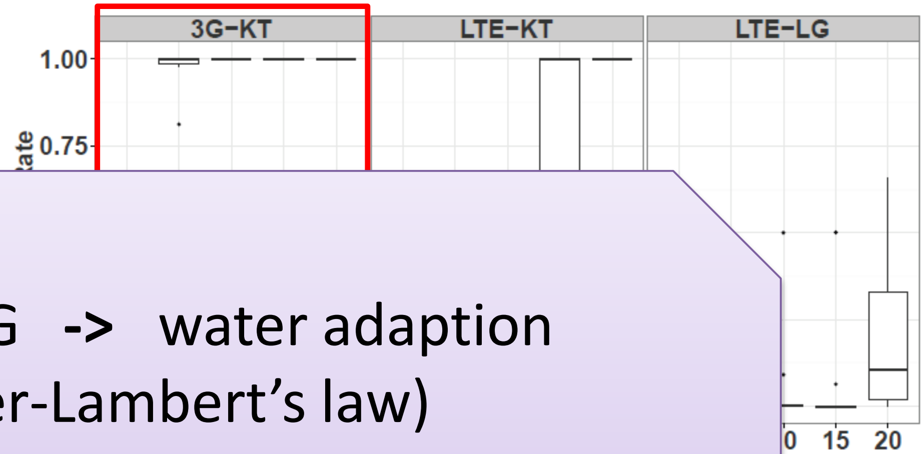


(b) RSS: LTE (KT and LG U+)

- WiFi
  - As water depth increases, RSS decreases.
- LTE
  - KT had consistently higher RSS values than LG U+.

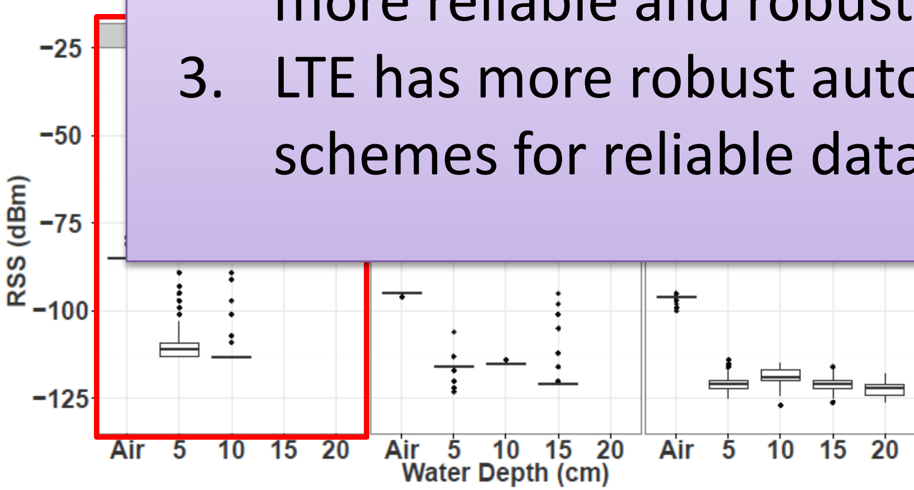
Measurement Results – 3G





Reasons:

1. frequency bands: LTE < 3G **->** water adaption coefficient: LTE < 3G (Beer-Lambert's law)
2. LTE uses multiple antennas making communications more reliable and robust.
3. LTE has more robust automatic repeat-request schemes for reliable data delivery.



(b) RSS: 3G and LTE (KT and LG U+)

not work well.

Network Reconnection Results - WiFi

- WiFi reconnection
  - Existing implementation: taking a long time:
    - AP scan interval (15 s)
    - Scanning time (1 s)
    - DHCP (1.8 s)
  - Our implementation (below 1 s):
    - Performing scanning immediately after disconnection (instead of waiting up to 15 s)
    - Reusing a previously assigned IP address (omitting DHCP)

Network Reconnection Results - LTE

- Significant differences between network providers
  - The mean reconnection latency of LG was much less than KT.

Reasons:

- LG U+ immediately recovered LTE connectivity
- KT always re-connected to 3G networks
  - Maintain 3G connectivity throughout current session.
  - Switch back to LTE networks when there were no packet exchanges.

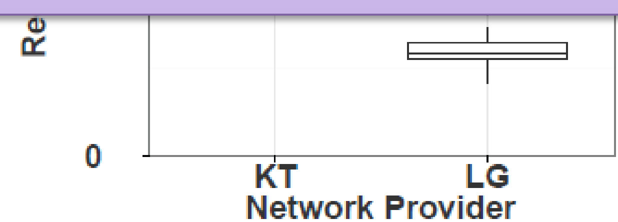
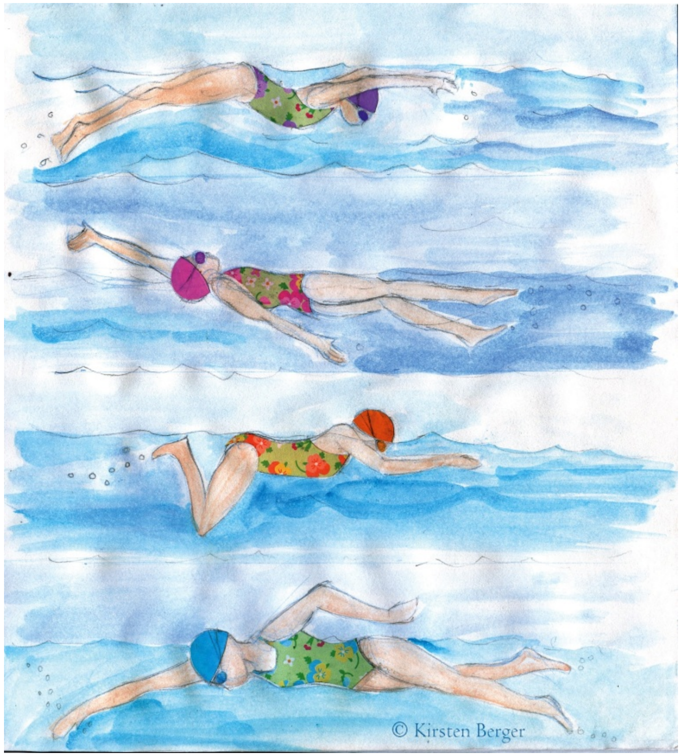


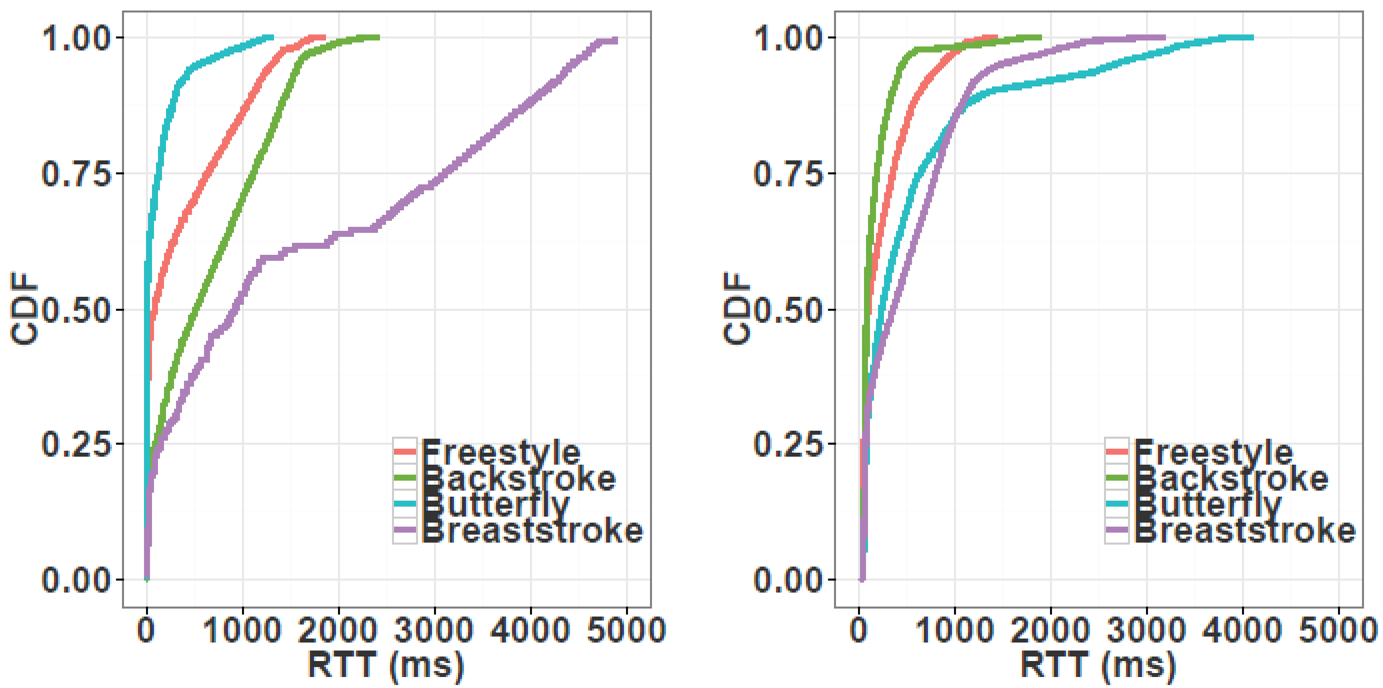
Figure 6: Reconnection time between LTE network providers (KT, LG)

Field Trial

- Goal:
  - Determine whether the different swimming strokes showed significant performance variations, as they have different levels of water immersion.
    - Freestyle
    - Backstroke
    - Butterfly
    - Breaststroke



Field Trial Results



(a) RTT CDF (WiFi)

(b) RTT CDF (LTE)

Figure 7: RTT CDF of WiFi and LTE (LG U+)

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Swimming Kinematics

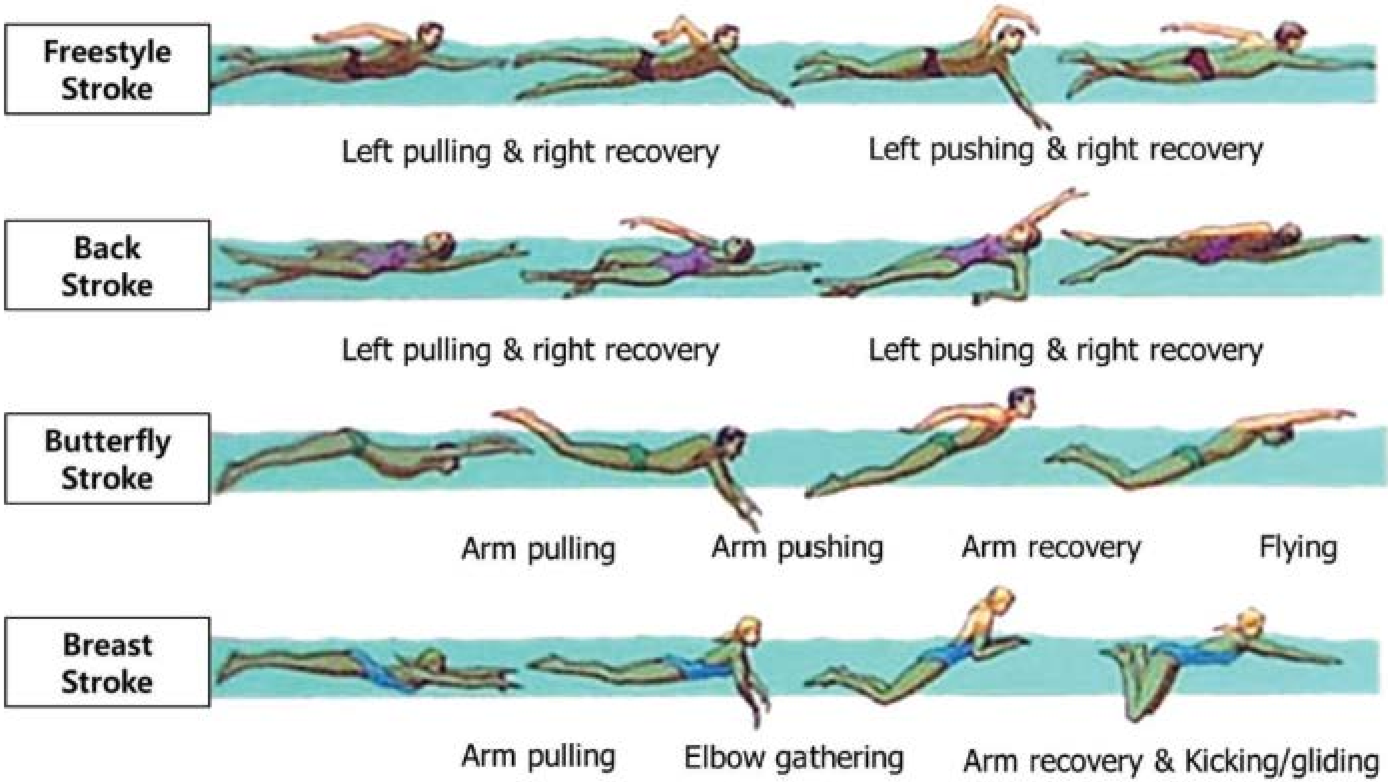


Figure 9: Illustration of stroke phase sequences. Arm pulling is common in all four strokes.

StrokeSense

- Function:
  - Recognizing two types of swimming action information: swimming style and stroke timing.
  - When an arm pull action is detected, StrokeSense reports the recently classified swimming style and the timing of the arm pull occurrence to the game logic.

Overview: StrokeSense

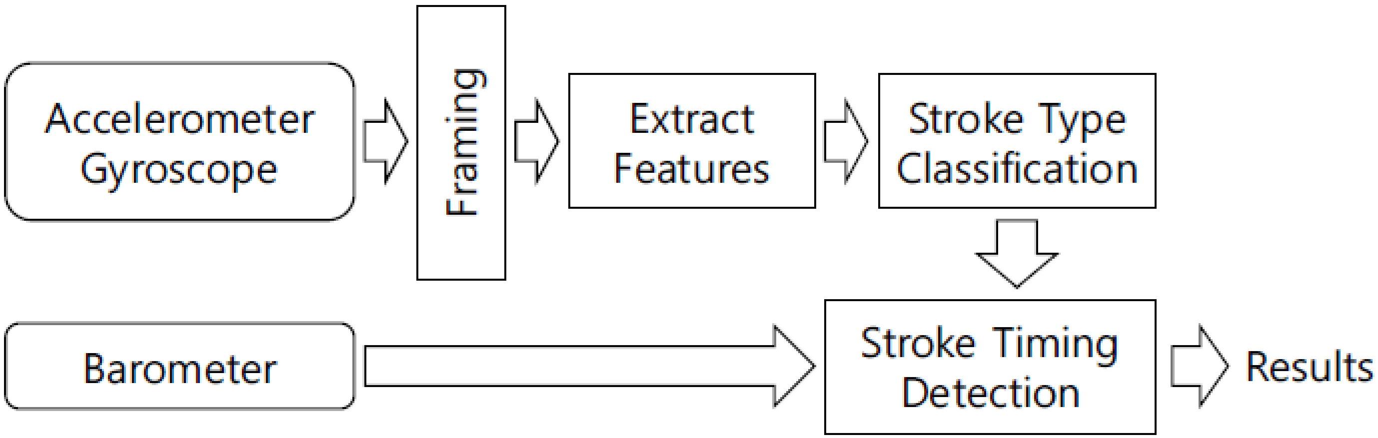


Figure 8: StrokeSense's data processing sequence

- Two types of swimming action information
  - Stroke type classifying: Accelerometer, Gyroscope
  - stroke timing Detection: Barometer

Data collection

❑ Experiment method:

- Sensors:
  - Motion sensors: accelerometer, gyroscope
  - Ambient pressure: barometer
- Smartphone:
  - CASIO G'zOne
- Where to place the smartphone:
  - Upper arm
- 11 participants
  - between 19 and 26 years old
  - swim two round trips for each stroke type

Collect what?
a. 3-axis accelerometer
b. 3-axis gyroscope
c. barometer data

Stroke Type Classification

- Feature Calculation:
  - 32 features

Table 1: Features used in swimming style classification

Measurement	Features
AccelX, AccelY, AccelZ, $\boxed{\text{AccelMag,}}$ GyroX, GyroY, GyroZ, $\boxed{\text{GyroMag}}$	Min, Max, Mean, Variance

Magnitude: The root-mean-square of the values from all three axes.

Stroke Type Classification (continue)

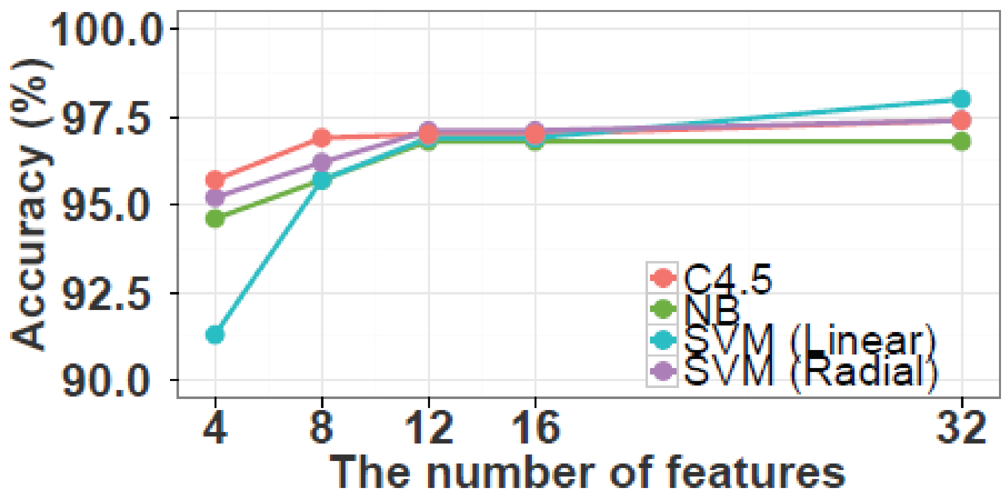
- Feature selection:
  - Correlation Feature Selection (CFS) algorithm: 16 features

Table 2: Selected features from CFS and their information gain (IG) scores

Feature	IG score	Feature	IG score
accely_mean	1.508	gyroy_min	0.699
accely_max	0.922	accely_variance	0.634
gyrox_mean	0.886	accely_min	0.632
gyrox_min	0.857	accelmag_variance	0.571
gyroy_max	0.778	gyromag_variance	0.543
accelz_min	0.739	gyroy_mean	0.482
gyrox_max	0.722	accelz_mean	0.321
accelx_min	0.721	accelx_mean	0.159

Stroke Type Classification(continue)

- Model
  - Decision Tree (DT)
  - Naive Bayes (NB)
  - Support Vector Machine (SVM)



- Evaluation
  - Train each model using the top 4, top 8, top 12, top 16, and all 32 features.
  - Validate the performance using 10-fold cross-validation.

Accuracy comparison:

- Our work: 98%
- Prior work:
  - wrist-worn accelerometer: 89.8%
  - upper back-worn accelerometer: 95.3%

Stroke Type Classification (continue)

- user-specific models
  - Use one user’s data

Participant	User-specific	Leave-one-user-out	Diff.
P1	98.51	94.67	-3.84
P2	98.36	97.41	-0.95

Conjectured reason:

- The similarity of arm movements in the swimming styles
  - i.e. Butterfly and freestyle sometimes showed similar crawling arm movements.

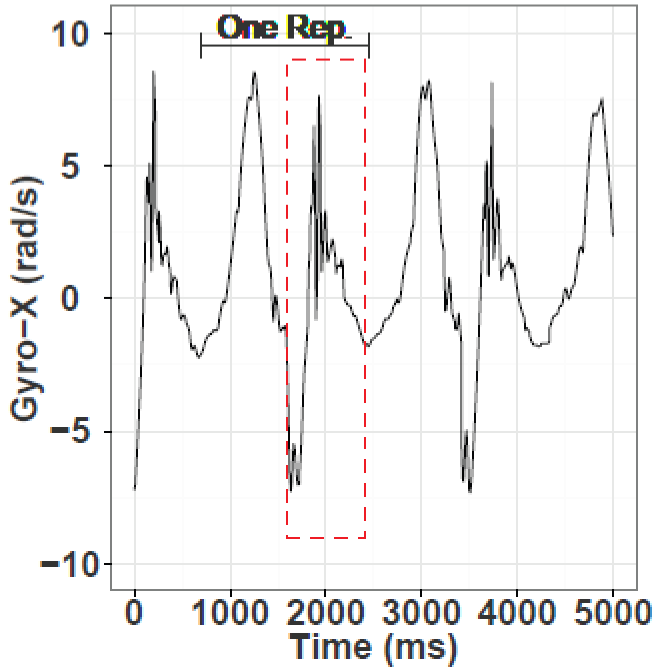
- lea
  mo
  - participants except for one for training.
  - Use the excluded one for testing.

confusion between butterfly and freestyle

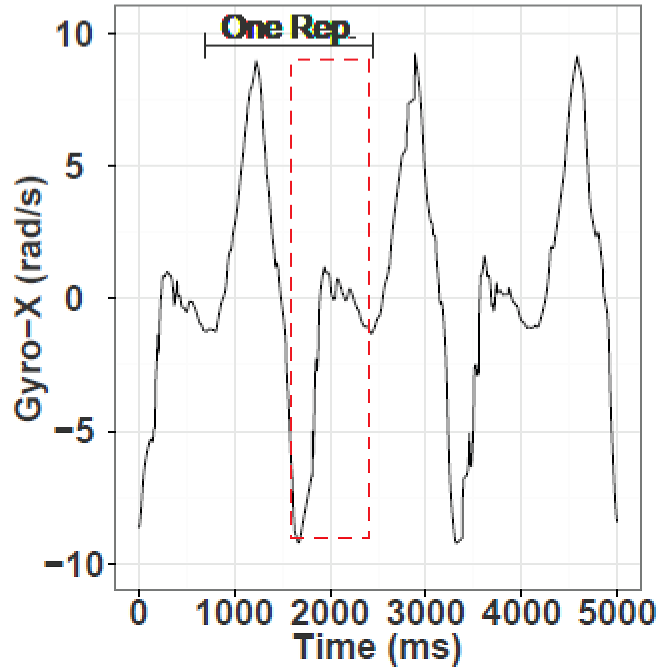
confusion between backstroke and breaststroke

Stroke Type Classification (continue)

- Motion sensor signal during butterfly



(a) Less trained casual swimmer



(b) Highly trained amateur

While swimmers are dragging up their arms, the arms of highly trained amateurs rotate more.

Stroke Type Classification (continue)

- Accuracy: (highly trained amateur model VS user-specific model)

Participant	Highly trained amateur	User-specific
A.P1	69%	100%
A.P2	50%	99%
A.P3	48%	95%
A.P4	53%	98%

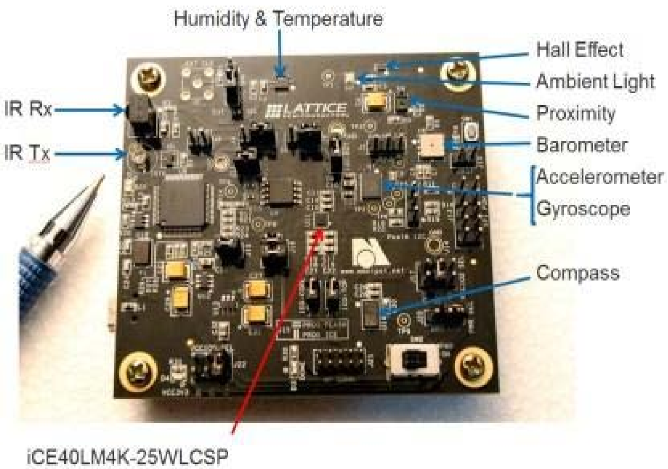
- Highly trained amateur: low.
- User-specific model: much better.

User-specific model can cover larger swimmer groups of swimmers, including less trained casual swimmers

Stroke Timing detection

❑ Data collection

- ➢ Sensor: barometer
  - highly periodic along with every stroke
  - highly robust against stroke type and swimmer-specific differences
- ➢ Data for analyzing
  - peaks in barometer signals
  - values
  - temporal sequences



❑ Robustness of the Barometer Signals

- ➢ Detailed motions
  - No significant changes in the signals. Why?
  - The signals are closely related to the water depth.
- ➢ Against personal differences in swimming motion

Stroke Timing detection (continue)

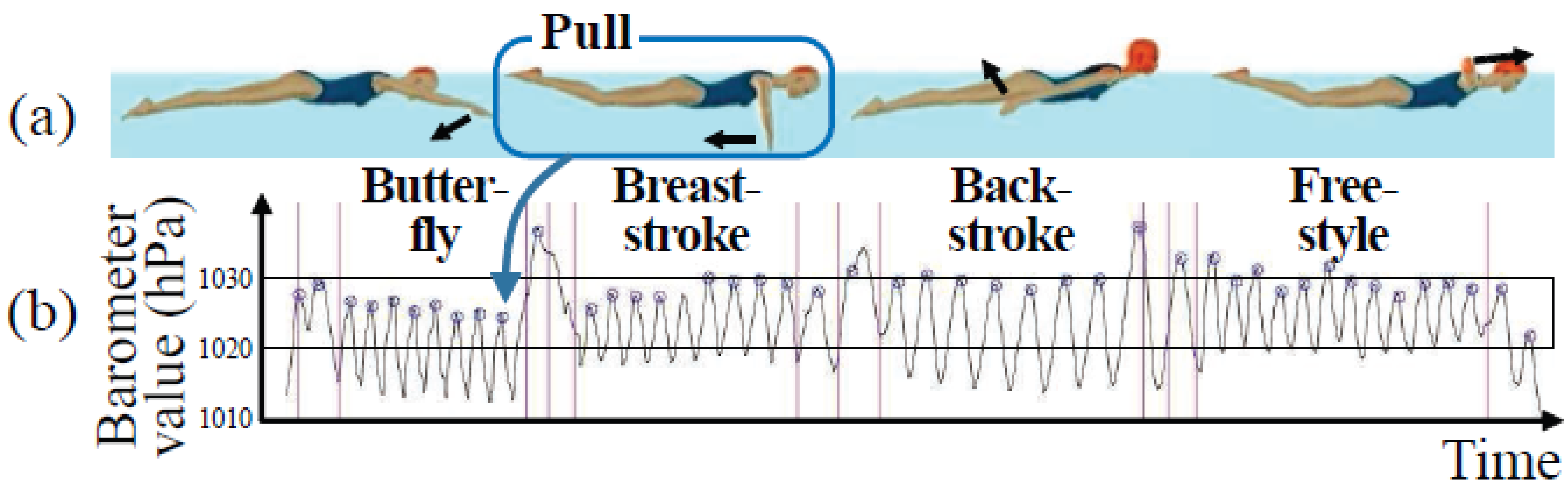
Algorithm Design

- **Smoothing:** Smooth Barometer data by averaging the most recent five samples to suppress high-frequency noises .
- **Finding:** Find local maximum and minimum peaks.
- **Reporting:** Report every significant local maximum peak as a stroke timing

Thresholds

- **Pressure threshold (2.5 hpa)**
  - The value difference between the recent local maximum and minimum peaks satisfies the pressure threshold, report the maximum peak.
- **Time threshold (1s)**
  - If significant peaks is detected, then ignore other ones until satisfying the time threshold.

Stroke Timing detection (continue)



Swimming Style	Ground Truth	TP	FP	TN
Freestyle	328	324	4	-
Backstroke	346	341	5	1
Breaststroke	435	378	55	11
Butterfly	359	353	6	-

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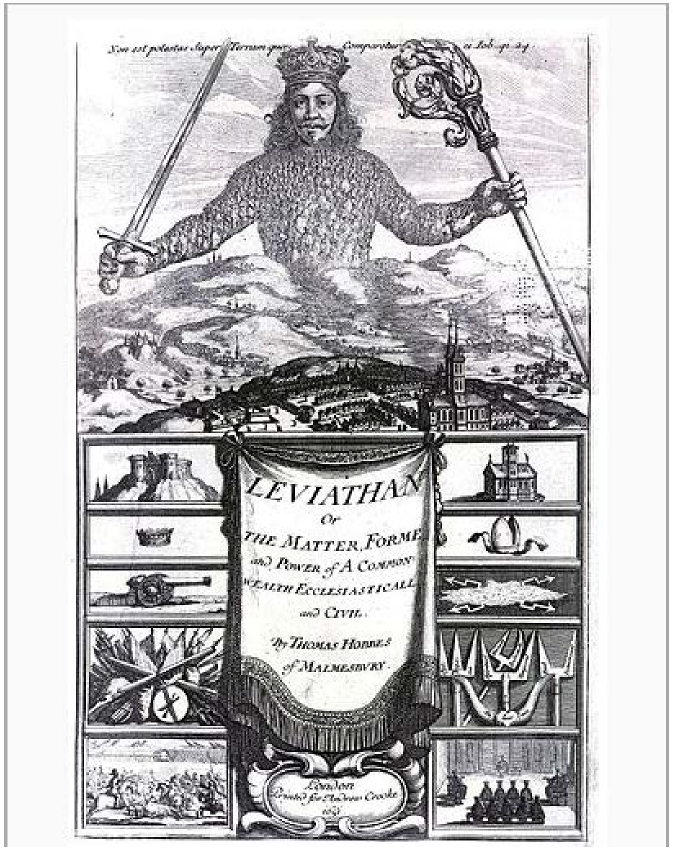
MobyDick: Overview

- What is it?

  A team-based hunting swimming game against a huge underwater monster, Leviathan.

- Property:
  - multi-player
  - Real-time
  - Underwater
  - Players can:
    - Attacking Leviathan
    - Evading the attack of Leviathan
    - Healing the wounded

Leviathan



MobyDick: Interaction Modalities

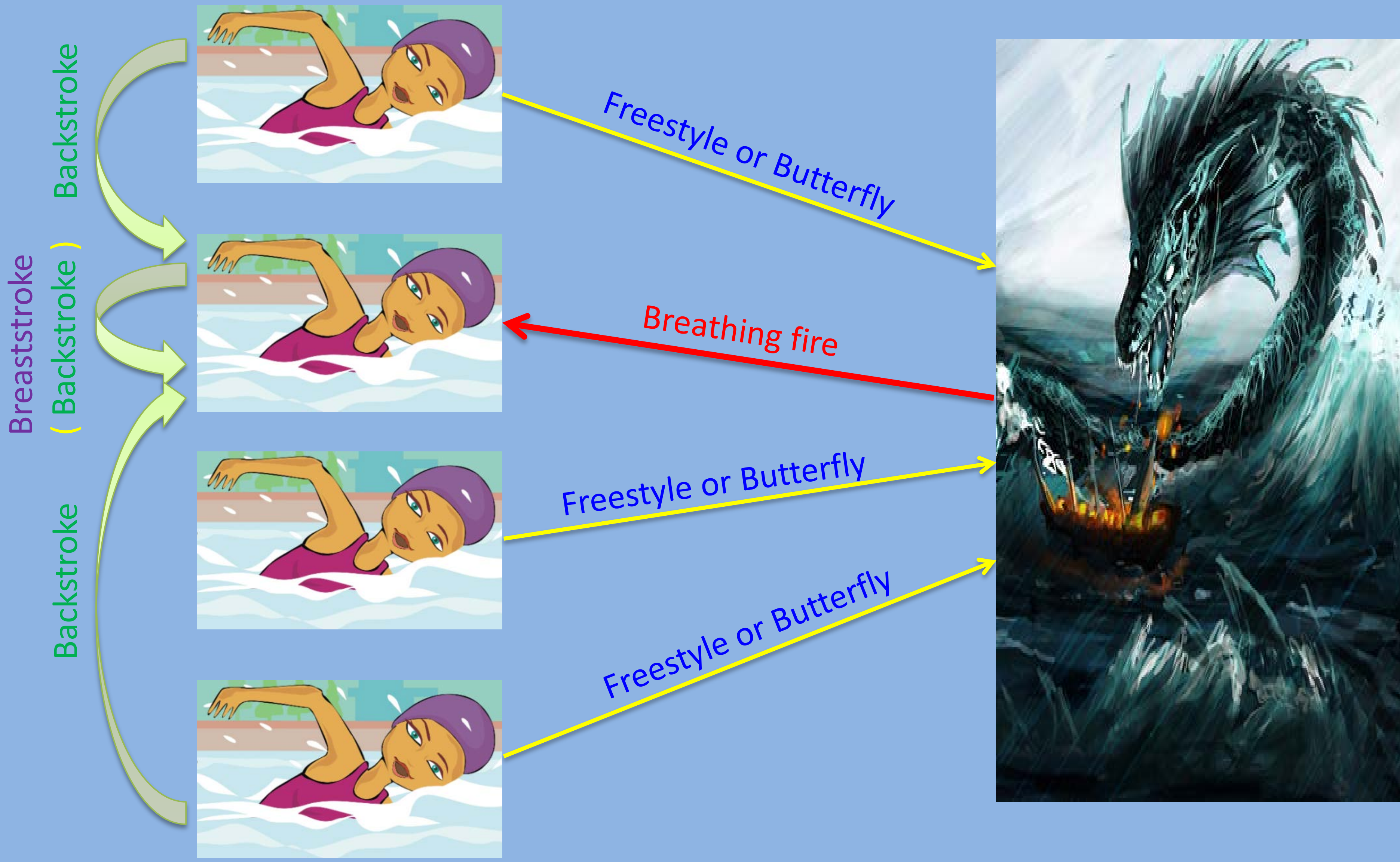
- Game inputs (smartphone: the swimmer’s upper arm)
  - Stroke timing
  - swimming style (freestyle, breaststroke, backstroke, and butterfly)

- Game outputs:
  - Auditory output (waterproof wired earphones)
    - Information:
      - game progress
      - team members’ status (health points…)
      - interaction events
    - Way: background music, narration, and sound icons

MobyDick: Game Design

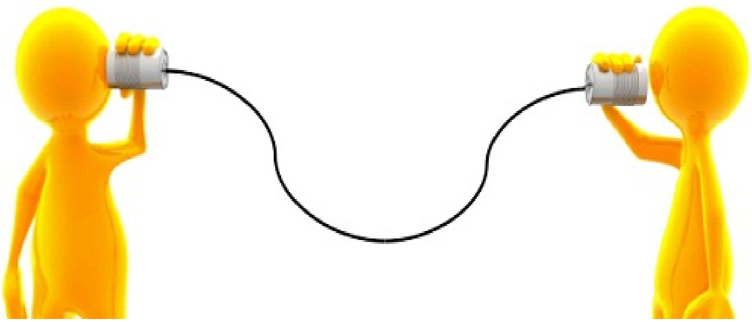
- A team: 4 swimmers
- One round time: 3 minutes
- Stroke type and distinct action category :
  - Freestyle: attack
  - Breaststroke: evasion
  - Backstroke: healing,
  - Butterfly: critical attack (Requiring higher level of mastery)
- Stroke events: Broadcast events in the background.
- Sound icon: Map each stroke with its own sound icon.
- In-game narrator:
  - It continually describes game progress, team members' statuses, and interaction events

MobyDick: Game Flow



MobyDick: Multi-player collaboration

- No explicit outbound communication
  - Get information from social awareness cues (the team-wide audio broadcast)



- Call sign for every swimmer:
  - Alpha, Bravo, Charlie, or Delta
- Performing strategic actions:
  - When something happens, each swimmer is expected to perform strategic actions based on their own decision.

MobyDick: Latency-aware game design

- Problem
  - Connectivity loss, long latency issues (critical for interactive game play)
- Solution
  - Hiding the accurate number of remaining health points, and representing them only in quartiles

    i.e. “Leviathan has less than 75% H.P.!”
  - Client locally computes one’s own status change (own death, revival)
    - Immediately notify the swimmer of the changes.
    - Remotely synchronize the server.
  - Moby-Dick clients inform and suggest stunned players:
    - You have been “stunned” and performing freestyle or backstroke for rapid recovery is recommended.

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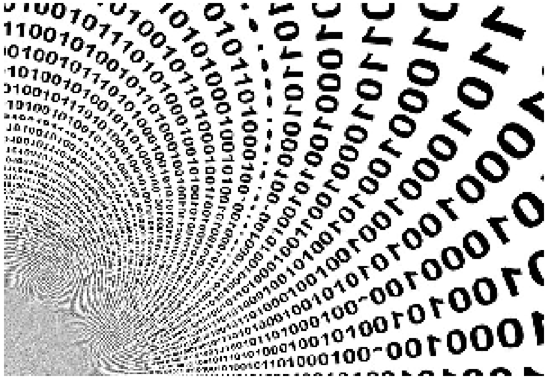
Implementation

- Modules
  - StrokeSense, Game logic, Communication
- StrokeSense module
  - Recognizing and reporting swimming style and stroke timing to the game logic.
- Game logic module
  - Managing the overall game and user interactions through game handler and user interaction manager respectively.
- Communication module
  - Managing Message exchanges.
    - Reliable UDP packet transmission schemes
    - Different Priorities for state messages
  - Monitoring wireless network connectivity



Measurement (user study)

- 8 participants:
  - More than one year of swimming experience
  - Swimming more than three times a week
  - Being capable of performing all four stroke types

Table 6: List of participants

Team	ID	Age	Gender	Experience
1	P1	23	F	2 years
	P2	20	F	4 years
	P3	22	M	3 years
	P4	23	M	5 years
2	P5	20	M	1 years
	P6	20	M	1 years
	P7	24	M	5 years
	P8	22	M	2 years

- 2 teams, 2 rounds of games for each team
- Focus group interviews followed by one-on-one interviews
- Recording video and audio of all the interviews
- Transcribing and coding the interviews

Measurement (results)

- Dissociation from intrinsic swimming activity
  - Enjoyable (all)
  - Certain degree of dissociation from swimming activity (most)
- Perceiving timely game responses
  - Immediate auditory feedback (6), Loud and clear sounds (all)
- Keeping track of game status updates
  - Most information (beginning), own information (end)
- Intuitive behavioral metaphor
  - The mappings between stroke types and in-game action is good.
- Socially enriched swimming experience
  - The unique mode of collaboration may create new feelings of bond and team spirit.
- Autonomous and dynamic team-play with social awareness cues
  - Having a potential to facilitate highly strategic collaboration, even without explicit communication channel.

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Discussion

- In the game, users tend to disregard others' information when they become tired. How to mitigate this problem?
  - Support pair-wise collaboration and competition in the game's content.

- Considering players' health, monitoring exercise intensity during the game is necessary. How to obtain this information?
  - Heart rate information can easily be translated into exercise intensity. So exercise intensity information can be obtained by monitor a swimmer's heartbeat using a special headset device.

- In order to solve the exercise intensity issue, what points do you think should be added or modified for the game.
  - Method 1: Provide an player-setting option for the maximum exercise intensity. During the game, if the player's exercise intensity reaches this threshold, warning him/her.
  - Method 2: Provide player-setting options , such as gender and age, before the game. The game can calculate an exercise-intensity threshold for each player. During the game, the game logic can monitor players' condition and warn them if necessary.

Discussion (continue)

- Does the research results in this paper benefit other areas?
  - Support pair-wise collaboration and competition in the game's content.

- For the work in this paper, are there any limitations? If yes, What are they?
  - The generalizability of this work. (Networking performance measurement was limited to two handsets and two operators)
  - Activity recognition may be not accurate enough. (only 11 participants, only one female)
  - Not comprehensive evaluation. (only a small number of participants (n=8))

THANKS !