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Students health physique information sharing in publicly collaborative services over edge-cloud networks

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Abstract

Data privacy is playing a vital role while facing the digital life aspects. Today, the world is being extensively interconnected through the internet of things (IoT) technologies. This huge interconnectivity is bringing very wonderful capabilities for improving the quality of life (QoL) with itself, for instance, in distributed healthcare. On the other hand, there are new challenges in the interconnectivity per use. One of the most challenging issues of IoT use in social systems and digital life is secure, trustable, and reliable interactions over IoT networks such that safety, security, and privacy in both aspects of cyber and physical worlds for humankind should be planned and controlled.

Due to the less physical activity of most people in the current world, fitness and aerobic sports are now an important need at any age to help them keep healthy in their cyber-physical life, specifically, for the younger student that are still in the growth ages. However, these sport activities need to be monitored seriously and closely to not put their life in danger. Herewith, healthcare services through IoT is becoming more applicable. Therefore, health information privacy for athletes is now a hot topic of investigation as we present the topic here. We propose an IoT-based physique healthcare system considering private information sharing for athletes based on data hiding at the edge of a collaborative system. The proposed system pays attention to the key factors of healthcare IoT infrastructure but it is bringing its new suggestions for more safety. Moreover, many evaluations based on different kinds of healthcare data are provided.

Keywords Edge computing, Cloud computing, Collaborative systems, Healthcare IoT (H-IoT), Public sports, Biosensors, Data privacy

Introduction

Every day we are observing new dimensions of smart sensors in our daily life. A rapid progress of deploying healthcare and biomedical personal devices has occurred recently for sports [1], such as mobile sensors for EEG/ECG analysis [2–4], and optical sensors for measuring blood pressure, heart rate, level of stress, and oximetry. Providing a remote, pervasive, persistent (real-time), and mobile health monitoring service is the main goal of such personal devices. The devices our normally implemented through either multipurpose gadgets or special medical devices, for example, heart rate monitoring by using smartwatch is a sample of multipurpose gadgets supported by a smartphone, whereas it can be also measured through a pulse oximeter as the special device. The current technology based on the advances in batteries and small-sized sensors and processors has been able to provide such devices for everyone, in particular, athletes.

Here, we only want to be concentrated on public sports and public health. One of the disappointing directions of

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utilizing technology in life is to face in activity and obesity. Therefore, the physicians are seriously recommending all students to spend part of their time for public sports. On the other hand, most students are non-professional about how to care their health while performing sport activities and exercises. It is very important to control vital signs and physiological reactions of the body while having hard physical activities, to not put people under the risk of heartbreak or other dangerous happenings. Two popular forms of sport activities that have received much attention in recent years among students are fitness and aerobic sports. As explained, it is very crucial to control the signs for such a goal on which as smart sensors should measure and collect the most important health data to use for risk evaluation, prediction of attacks, and to manage the activities, e.g., for treating obesity. Normally, the collected data are processed locally by an AI system to alert directly, but it is sometimes required to share the data over communication networks with a physical education trainer or even physician either online or offline.

Technically, the most applicable signals and measurements with a smart biosensor are Electrocardiogram (ECG), Electroencephalogram (EEG), and Photoplethysmogram (PPG) in modern devices to make the H-IoT physical layer. ECG signals are used for analyzing the heart performance based on cardiac cycles. The ECG signals are collected by using electrical measurements with a direct contact of skin and the sensors' electrodes (at least two). EEG is similar to ECG in terms of the type of measurements, i.e., electrical bio-signals. Normally, both ECG and EEG can be functionally measured over time for real-time monitoring of heart and brain, respectively. Their signals are one-dimensional data as a function of time. In addition, EMG signals are for electromyography [5], that is the same as these two, but not as popular as ECG and EEG for public sports. For ECG and EEG measurements, the wearable devices (gadgets) need a skin contact. Recently, smart head-cap and headband technology has been a strongly developed towards smart mobile EEG sensors for diagnosis and prognosis of neurological disorders.

ECG can be easily measured by smart watches or smart clothes. On the other hand, PPG signals are measured optically by using variable sensors such as smartwatches and pulse oximeters. PPG has made a big advancement and fantastic capability for pervasive and remote healthcare and on-demand monitoring. PPG is similar to ECG and EEG for non-invasive use and may be able to control some signs that are obtainable through the other sensors as well, e.g., heart rate. However, measuring the oxygen saturation level (SpO2 in pulse oximetry), and blood pressure is the new ability of wearables and gadgets that has been possible with the help of PPG [6]. For more information about some personal devices for health monitoring including usual H-IoT devices and gadgets refer to the list below.

- EEG headband connected to smartphone for meditation (https://www.amazon.com/gp/aw/d/B07HL2S9JQ)
- A Samsung smartwatch to measure heart rate (https://www.samsung.com/us/watches/)
- smart ECG wearable [7]
- Portable pulse oximeter with PPG measurement (https://www.uem-mall.com/products/portable-pulse-oximeter-with-oem-service?)

In addition to the biosensors discussed, many other wearable sensors such as GPS and accelerometer, which are placed on popular devices of people, mainly smartwatch and smartphone are providing useful and essential information about the quality of activities in fitness [8]. In Results section, some outputs of biomedical and general sensors for fitness exercises are provided.

Our motivation

The fitness information of every athlete is generally private and must not be shared publicly; this is a rule that should be seriously followed. On the other hand, utilizing a few smart sensors that are connected to a health-monitoring network will bring its concerns about private information sharing. The ecosystem of medical internet of things (M-IoT) or H-IoT provides a comprehensive platform for all directions of data communications and processing over networks. The personal gadgets of athletes including smart watches and clothes would be at the edge/things layer of M-IoT where a smartphone is at the edge/fog layer. It is preferred to use wireless links through a wireless body-area sensor network (WBASN) to connect sensors to each other, the network gateway, and local processors. This is because the athletes must be fully flexible after placing the wearable sensors on their bodies. Among all biosensors, only some types of ECG sensors may be wired in working structure, but this wired structure is not related to their generality of the wireless networking. In short-range communications between the data collecting sensors and edge/fog processors, Bluetooth or similar short-range communication technologies is used that optimistically guarantees the private sharing.

For example, assume a smart watch is being used for measuring ECG pattern periodically, some processing of signals is done by the processor of the watch locally, it is considered to be computing at the things layer which is centralized without needing data sharing, so this communication is inherently private. Now, assume for ECG visualization and interpretation, smartphone must help the watch as an edge server having more computing capability, thus there will be a short-range wireless link between the watch and the phone. Also, supposed that the AI algorithms in both smartwatch and smartphone are unable to interpret the ECG reports to predict a possible heart attack, there will be a need to stronger AI processors or maybe a human expert that are not there. In such a condition, long-range transmission as either wireless, wired, or hybrid exists. Therefore, more relays, receivers, and observers might be included in long-range sharing.

In order to guarantee the private sharing, data hiding techniques to hide entity information of athletes are required. The hiding techniques can hide personal information of students into their sport-health/medical reports reversely to not be visible for non-audience/unauthorized receivers. In addition, data hiding is a trustable way for medical documentation and management. Here, all data are visual even EEG and ECG signals, because it was assumed that the edge processors (the microprocessor of smartphone and the installed software in it for recently explained example) could visualize all sensed data to share for advanced interpretations. Thus, the shared information is not a one-dimensional data, it is completely visual as a digital image. Reversible image data hiding is used for making privacy here. The main goal of our research is not security and robustness, therefore data hiding techniques do not require to be robust against attacks or to be combined with cryptography techniques. A good selection is lossless data hiding (LDH) strategies based on interpolators. In next section, a review on these strategies is presented.

The information here is continuous-time, dynamic, behavioural, and functional in terms of time. Visualizing such information itself needs advanced techniques [8]. This part of the process is not studied in our research and we use the existing technologies that can make the fitness visual information [8], or smart sensors that are supported by a mobile application with the ability of automatic visualization. As a concise conclusion, the main contributions of this work are listed as follows:

- Study of the importance of visual computing for IoT devices in healthcare and sport use.
- Description of a suggested IoT-enabled edge/cloud infrastructure for sport medicine.
- Evaluation of LDH techniques for different visually illustrated biomedical data.

Organization

The rest of the paper is presented as follows. In Lossless data hiding for privacy: methods and measures section, the data hiding strategies will be reviewed. The proposed private architecture based on data hiding and edge-cloud computing is presented in The proposed architecture section. Results section provides the required evaluation and results to examine the purpose architecture. The last section is Conclusions.

Lossless data hiding for privacy: methods and measures

Data hiding in digital images is a solution for different goals. Data hiding can be used for data compression and communications [9], data security [10], copyright protection [11], data management [12], and so on. Secure data hiding methods have various categories, for example, some are performed along with data encryption that are mostly known as steganography [13] whereas some are very simple. The use for privacy in this paper is an aim at the middle of data management and security.

One of the high-performance data hiding techniques in digital images is lossless data hiding (LDH), or reversible data hiding. The most important properties of this type of data hiding for data management is hiding capacity and host quality [12]. However, in other uses such as data privacy and data communications [14], the capacity is the most important property of data hiding techniques. Here, there is no attack, so robustness is not followed as a goal. Among the data hiding methods, interpolation-based techniques are very popular. In this taper, a data hiding technique in this type is utilized. As follows, a brief review on how to test a hiding process based on measures is presented, then a review on a few interpolation-based lossless data hiding methods is given.

The hiding capacity in digital images is mostly measured in terms of bit per pixel (bpp). For computing the capacity, the number of hidden bits is divided by the number of pixels in the host image. Data hiding is a kind of data fusion; therefore, the measures of multi-source compression can be usable in some problems. The average capacity formula is according to Eq. 1.

$$\bar{C}_{Gray}(bpp) = \frac{H_{Gray}}{M \times N} \tag{1}$$

Where H (in terms of bit) is the number of hidden bits. M and N are dimensions of a gray-scale image used at the host. For color hosts, the hiding is done separately in each layer of RGB image. Equation 1 is corrected for color images as follows, Eqs. 2 and 3.

$$H_{RGB}(bit) = H_R + H_G + H_B \tag{2}$$

$$\bar{C}_{RGB}\,(bpp) = \frac{H_{RGB}}{3 \times M \times N} \tag{3}$$

For interpretation of the average capacity results, it is enough to say that higher amounts means a better performance. As a result, the average capacity is a linear measure of evaluation of data hiding methods in private data sharing.

In order to a review on interpolation-based data hiding methods, it is noticeable that they are not limited to 2D forms for digital images. In other words, 1D forms for signals might be applied, even though we consider all visual data of fitness as a gray-scale or color image. There are many recently suggested data hiding techniques based on interpolation [15]. Most of them use non-adaptive computations. Fundamentals of the interpolation-based data hiding returns to an idea that is known as differential expansion that is a very popular and strong strategy to design high-performance methods [16]. For modifying interpolation-based data hiding, a common way is to enhance the host's histogram [12]. The interpolator in [12] is a nonlinear operator while many other LDH techniques prefer to use the linear forms.

In [17], a data hiding technique based on linear interpolator was proposed that is not as strong as nonlinear interpolators in terms of capacity-based and visual performance. The nonlinear interpolators outperforms the linear ones because of the use of adaptive computations based on the local observations. The linear interpolators do not behave in the same way. In [18], a new interpolation-based data hiding solution by using parabolic interpolation has been suggested. The proposed technique in that paper is not lossless and its interpolator is not eventually attending to the local distribution in images because the parabolic interpolators is a linear and non-adaptive interpolating filter for digital images. For both reasons, this recent method is not a big progress even though the used interpolator is fresh in its type. The new method of interpolation based on parabolic theory has been investigated in two additional papers as well [19, 20]. Maybe these two techniques could be considered as a modified form of the technique suggested in [18], because not only the final data hiding method is lossless, but also they could implement the complete form of parabolic interpolation. Anyway, all of these reviewed solutions are not adaptive and could not compute the local estimations required for their data hiding algorithms.

In interpolation-based data hiding techniques, usually there are two components including interpolator and data hiding function (engine). Here, we select two high-performance components for both parts. The engine is selected similar to [15], and interpolator is similar to [12]. This lossless data hiding technique is tested in the application of this research (Results section). To have a general look, its properties have been taxonomically listed in Table 1.

In The proposed architecture section, the details of the proposed strategy for private data sharing in edge-cloud networks using the data hiding technique discussed here will be presented.

The proposed architecture

In Lossless data hiding for privacy: methods and measures section, a general review on the data hiding used in the proposed architecture, was introduced for obtaining a trustable comprehensive systematic architecture to guarantee private information sharing in joint public sports-healthcare systems. The proposed architecture includes all physical and cyber components of an applied cyber-physical system (CPS). The focus of THE novelties in this paper is on the architectural design, and evaluation aspects. However, the role of communication networks would be a specified in the architecture. Figure 1 provides a general consecutive schematic of the common IoT/cloud-based healthcare services. Our system (Fig. 2) is an interpretation of Fig. 1.

Figure 2 indicates which components exist in the architecture and how they are working with each other to make a possibility of data privacy and private information sharing over an edge-cloud network [21–25]. The edge-side data links should be wireless to not make any problem for athletes. This network of the CPS components including networking (communications) nodes and computing nodes (processors/servers, e.g., towards recommendations [26, 27]) realizes the H-IoT in first structure. Explaining the components in Fig. 2 is very important to draw a proper understanding of how this purpose system works efficiently.

The components

Here a description of all components is listed to explain how they are enabling the unified system to make a private interaction.

Athletes: the body of athletes is a place to deploy some sensors; these sensors will monitor the various aspects of the athletes health. In addition, the athletes not only are a source of biological sensing, they should be informed

Table 1 This table provides the general properties of the LDH method used

Application	Differential expansion-based	Interpolation-based	Reversibility	Filtering
Digital Images	Yes	Yes	Lossless	Nonlinear

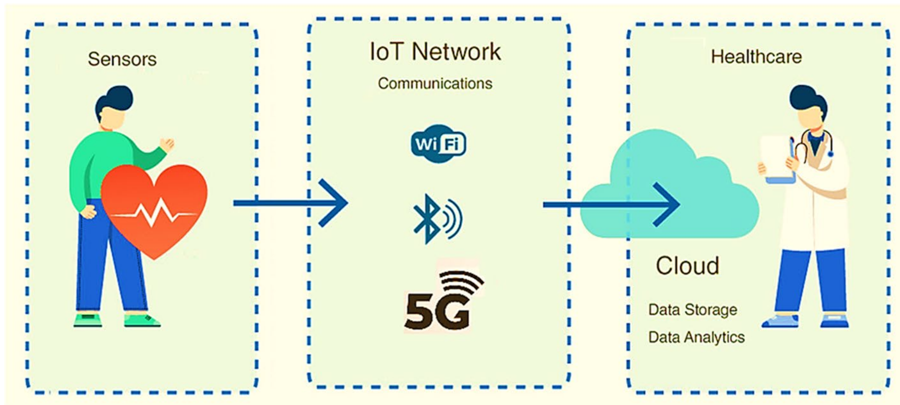

Fig. 1 General H-IoT schematic in the known literature

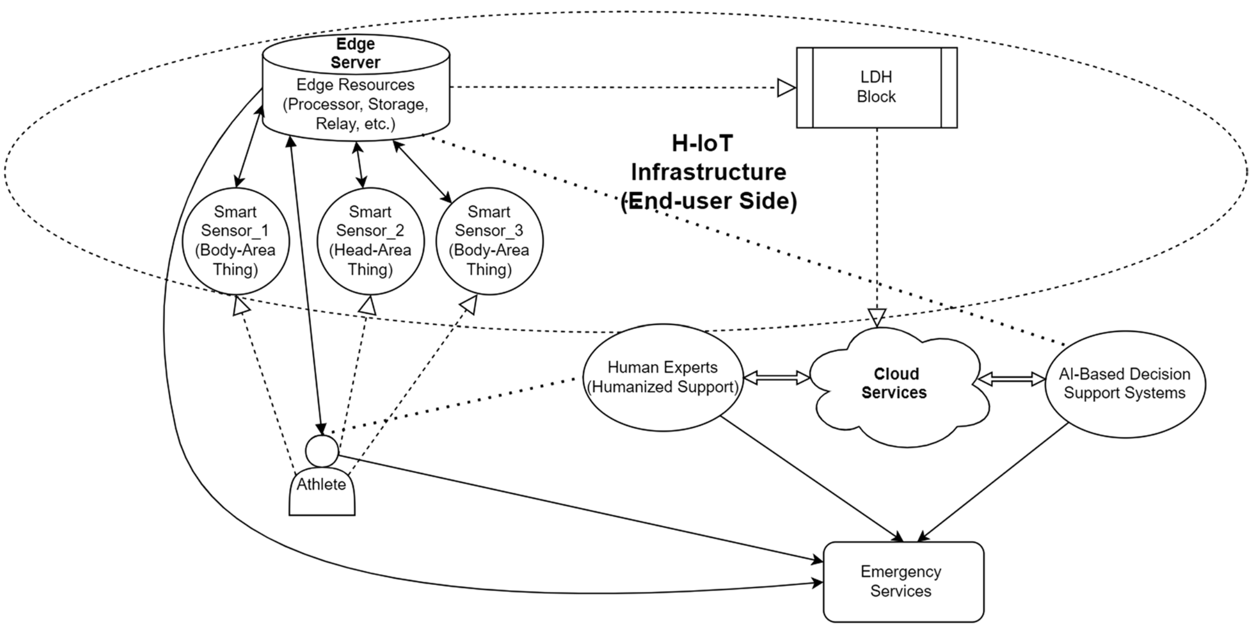

Fig. 2 The proposed collaborative architecture for H-IoT in public sports

about their health condition after technical interpretations and data analysis in real-time or offline. The feedback to the athletes may contain both forms of offline feedback (for non-critical situations) and on-demand real-time/immediate alarms (for critical situations like possible heart attack). The feedback to the athletes may be detailed reports generated by an AI-based decision support system or a coach/physician.

Smart sensors and edge services: there are several wearable sensors placed on clothes, smartwatches, headbands, and so on, to collect the health monitoring data by using exact measurements. Smart sensors are benefiting from local processors that enable them to do some low-level computing at the things layer of H-IoT. There are two different types of connection between the sensors and outside, including a biological path utilizing bio-electrical, bio-optical, and bio-chemical interfaces (between the sensors and the body), and a wireless connection between the sensors and the server, here a smartphone with the supporting apps to work with the sensors effectively. The sensors are a main physical part of cyber-physical healthcare systems for sensing and human-machine interfacing (HMI) whereas the smartphone will act more widely.

(1) cyber role as an edge server for computing and local storage.

(2) cyber role as a relay node to communicate data.
(3) physical role as actuator/detector for making alarms and data visualization.
(4) physical role as sensor (GPS, imaging, etc.).

LDH block: lossless data hiding block is the realization of data privacy based on computational techniques. In the designed architecture, the short-range wireless links between the smart sensors and the edge server can be ignored as an obstacle against private information sharing. It is because not only the range is very limited, the data can be coded to not be visible for a near listener, and just two nodes are defined to access it based on an agreement, i.e., the smart sensor and the server. Nevertheless, when the server decides to send the health or biomedical data to a third party with long-distance centres to be more processed, the data must not be coded to be readable and interpretable by unknown third parties, for example, other experts in the medical support centres. But entity of the athletes is not required for some who have access the data, therefore a technique for private sharing based on LDH block is required. Some experts may be allowed to access the entity of the athletes or patients, however some may not be. The LDH block will insert the entity information into the medical data and share to all receivers, but as per an agreed protocol, the authorized receiving nodes, either human or AI, can extract the entity information. The LDH block's role is somewhat like an encryption algorithm, but there is a big difference between these two. For sending the entity information along with some medical data records related to the athletes, a data encryption strategy will need to first encrypt the supporting data. Then the data is sent as a separate file, whereas the LDH block will not need to use a separate supporting file for sending, it will hide the supporting data into the visual medical information.

Cloud server, AI-based decision support system, and the human experts: advanced computing and final interpretations are performed by this unit. An unauthorized third party with useful expertise may be here, that its service is essential medically. Therefore, part of this unit might not be permitted to access the entity information.

Emergency services: this part is the last unit in this architecture; this service might be contacted by either athletes, edge servers, or cloud servers for urgent biomedical care in critical situations.

The unified procedure of the proposed architecture with sequential steps is eventually provided in eight steps, as follows:

1. Bio-sensing
2. Local information processing, and reporting at the things layer (considering low-resource devices)
3. Information processing at the edge and reporting
4. Determining non-interpretable information
5. Signal transformation and preparing visual information
6. LDH process for privacy
7. Information sharing (long-range)
8. Cloud-based analytics and reporting

And a pseudocode to describe the main approach is seem below

Pseudocode of the proposed system for the stages 5 to 7

```
Input : Health Information (H)
Input : Private Entity Information (P)
Host Selection :
If H is not visually 2D / 3D image
        X = f(H)   //   f is converting non – visual to image
Else
        X = H
Private Hiding and Transmission:
        X_h = X + P
Output : Integrated Information (X_h)
```

Results

This section aims at presenting the simulation results of data hiding for the H-IoT data of public sports. Three types of sport data as visual information for transmission over the edge-cloud networks have been used for tests as our dataset. They include aerial images indicating the direction maps based GPS and vision systems (first dataset), visualized information recorded by wearable biosensors for heart rate and move (second dataset), and a modern case of ECG reports from *Samsung* smart watches (third dataset).

The first two are coming from a past research, entitled "Visual analysis of users' performance data in fitness activities" [8], we credit its authors for their helpful research. All three groups of data are considered as digital images and are named "GPS_MAP, Visualization, and ECG", respectively. As the goal of this research is specific in its type, the number of tested data, although is limited, does not affect the comprehensiveness of the achievement. Figures 3, 4 and 5 shows the samples of the three sets, respectively.

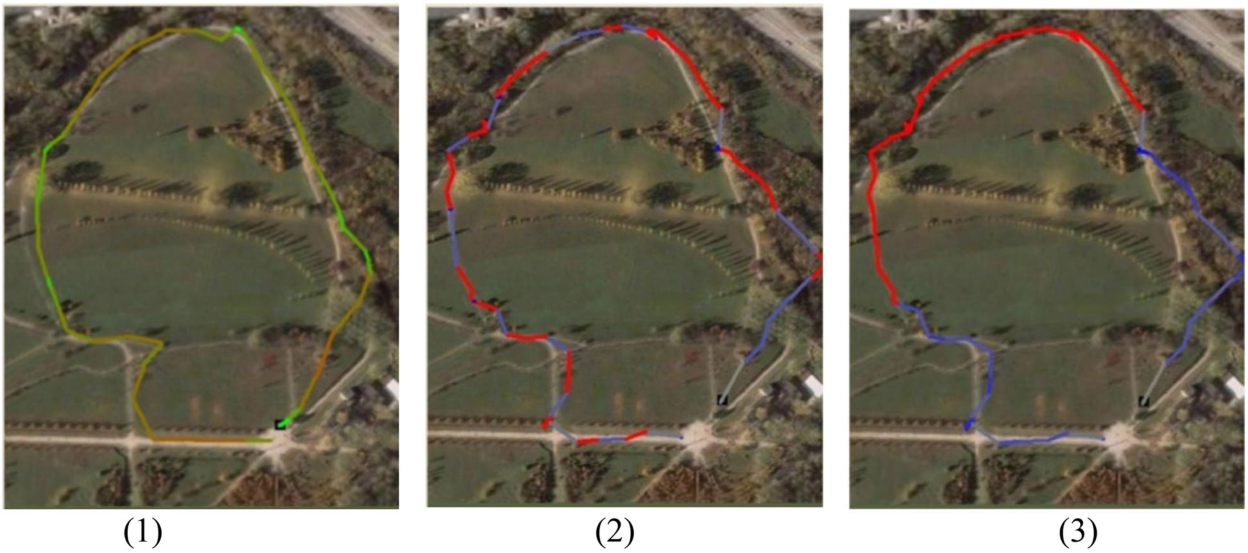

Fig. 3 The samples of Dataset_1 (GPS_MAP)

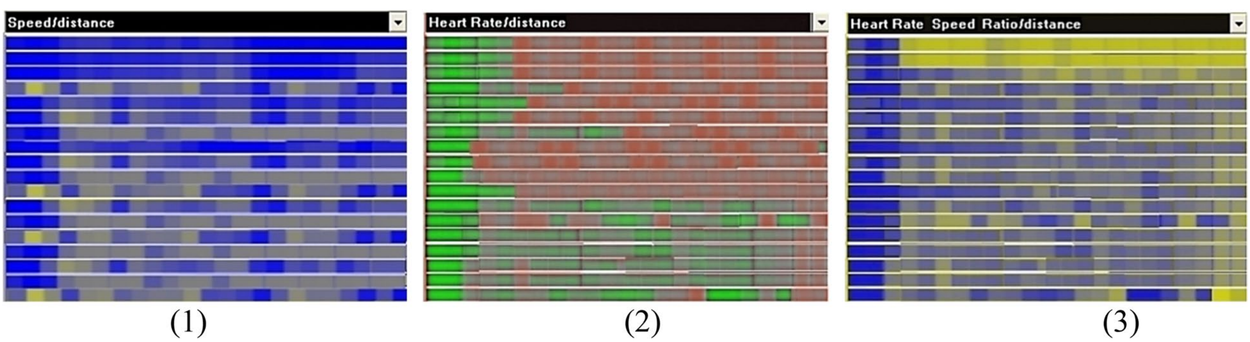

Fig. 4 The samples of Dataset_2 (Visualization)

The extended metrics

To understand the results in Tables 2, 3 and 4, the normalized-per-pixel capacity (in bpp) of each layer of a color sample in RGB space is according Eq. 1, but we rewrote it separately for RGB layers in Eq. 4. The normalized capacity for the whole of color image is according Eq. 5 that is another representation of Eq. 3 by using Eq. 4.

$$C_R\,(bpp) = \frac{H_R}{M \times N}$$
$$C_G\,(bpp) = \frac{H_G}{M \times N} \tag{4}$$
$$C_B\,(bpp) = \frac{H_B}{M \times N}$$

$$\bar{C}_{RGB}\,(bpp) = \frac{C_R + C_G + C_B}{3} \tag{5}$$

An average of the normalized capacity (in bpp) for each dataset is computed based on its samples; Eq. 6 indicates the averages that are used in the next computations. For computing standard deviation of each dataset, Eq. 7 is first used to find variance.

$$\bar{C}_{set1} = \frac{\bar{C}_{RGB\_sample1} + \bar{C}_{RGB\_sample2} + \bar{C}_{RGB\_sample3}}{3}$$
$$\bar{C}_{set2} = \frac{\bar{C}_{RGB\_sample1} + \bar{C}_{RGB\_sample2} + \bar{C}_{RGB\_sample3}}{3}$$
$$\bar{C}_{set3} = \frac{\bar{C}_{RGB\_sample1} + \bar{C}_{RGB\_sample2}}{2} \tag{6}$$

$$\sigma^2 = \begin{cases} (\bar{C}_{RGB,sample1} - \bar{C}_{set\ i})^2 + (\bar{C}_{RGB,sample2} - \bar{C}_{set\ i})^2 & \mathrm{i} = 3 \\ \frac{(\bar{C}_{RGB\_sample1} - \bar{C}_{set\ i})^2 + (\bar{C}_{RGB\_sample2} - \bar{C}_{set\ i})^2 + (\bar{C}_{RGB\_sample3} - \bar{C}_{set\ i})^2}{2} & \mathrm{i} = 1, 2 \end{cases} \tag{7}$$

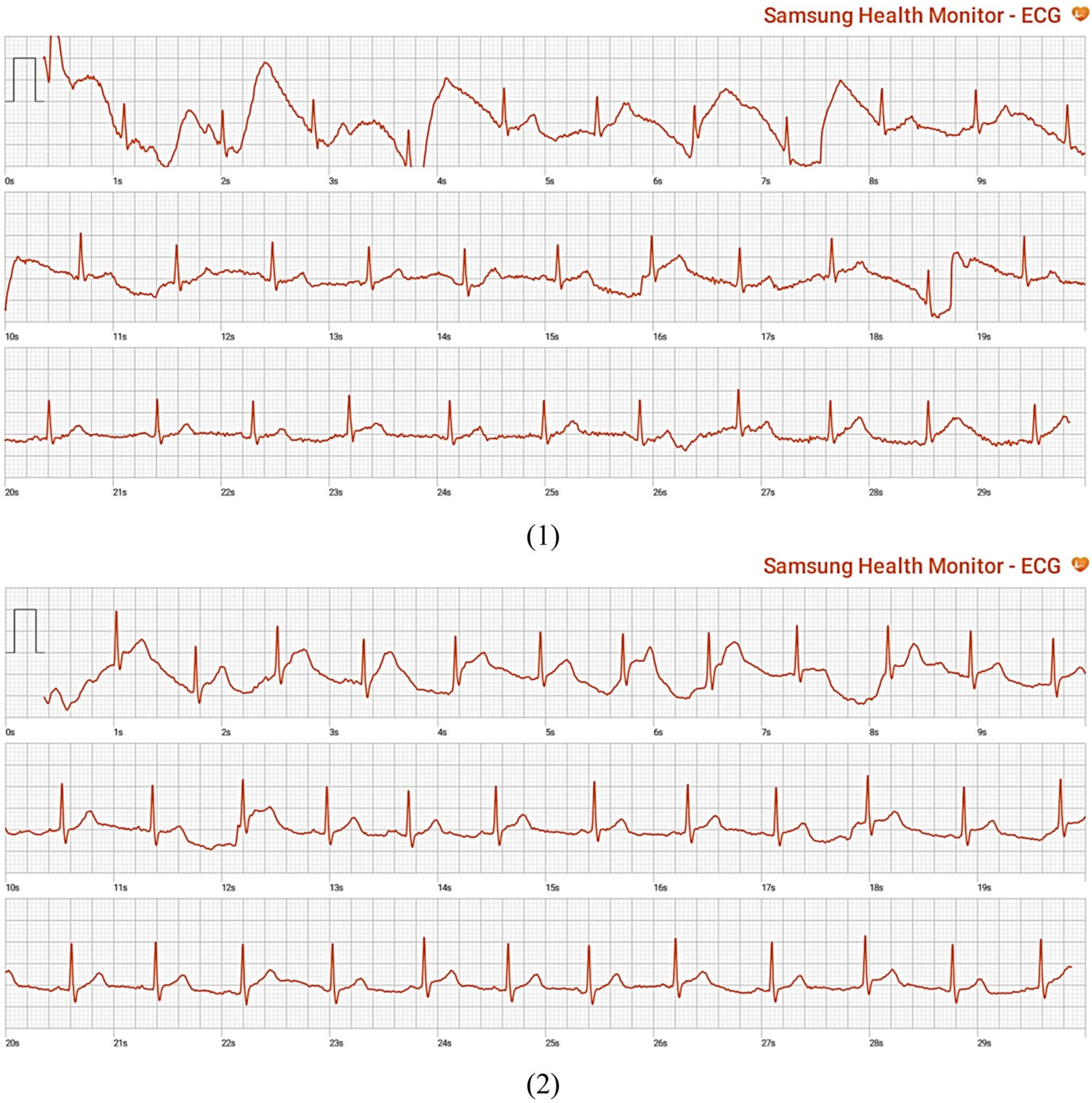

Fig. 5 The samples of Dataset_3 (ECG)

Table 2 Results of for Dataset_1 (GPS_MAP)

	H_R (bit)	H_G (bit)	H_B (bit)	H_{RGB} (bit)	Sample's size (2D)	C_R (bpp)	C_G (bpp)	C_B (bpp)	$\overline{C}_{RGB}$ (bpp)	STD
Sample1	159612	160887	156,728	477,227	468 × 598	0.5703	0.5748	0.5600	0.5683	-
Sample2	131527	133039	130813	395379	468 × 598	0.4699	0.4753	0.4674	0.4708	-
Sample3	133,670	137,803	130,231	401,704	468 × 598	0.4776	0.4923	0.4653	0.4784	-
Average	141,603	143,910	139,257	424,770	-	-	-	-	$\overline{C}_{set1} = 0.5058$	0.0538

Table 3 Results for Dataset_2 (Visualization)

	H_R (bit)	H_G (bit)	H_B (bit)	H_{RGB} (bit)	Sample's size (2D)	C_R (bpp)	C_G (bpp)	C_B (bpp)	$\bar{C}_{RGB}$ (bpp)	STD
Sample1	410531	410508	374342	1,195,381	910×650	0.6940	0.6940	0.6328	0.6736	-
Sample2	370674	367344	366053	1,113,071	910×650	0.6266	0.6210	0.6188	0.6221	-
Sample3	380959	382543	343537	1,107,049	910×650	0.6440	0.6467	0.5807	0.6238	-
Average	387,388	389,798	361,311	1,138,500	-	-	-	-	$\bar{C}_{set2}$ = 0.6398	0.0293

Table 4 Results of for Dataset_3 (ECG)

	H_R (bit)	H_G (bit)	H_B (bit)	H_{RGB} (bit)	Sample's size (2D)	C_R (bpp)	C_G (bpp)	C_B (bpp)	$\bar{C}_{RGB}$ (bpp)	STD
Sample1	702362	670647	669960	2,042,969	1752×820	0.4889	0.4668	0.4663	0.4740	-
Sample2	701416	668794	668,061	2,038,271	1752×820	0.4882	0.4655	0.4650	0.4729	-
Average	701,889	669,721	669,011	2,040,620	-	-	-	-	$\bar{C}_{set3}$ = 0.4734	0.0078

Table 5 The overall description of all results for three tested datasets

Measures	$\bar{C}_w$	*Weighted STD*
Results for All Samples	0.5479	0.0772

Since the datasets are not the same as each other for the sample counts, a weighted form of the measures has been computed in Eqs. 8 and 9, and finally the standard deviation in general form is from Eq. 10.

$$\bar{C}_W = \frac{3 \times \bar{C}_{set1} + 3 \times \bar{C}_{set2} + 2 \times \bar{C}_{set3}}{8} \quad (8)$$

$$\sigma_w^2 = \frac{3 \times (\bar{C}_{set1} - \bar{C}_W)^2 + 3 \times (\bar{C}_{set2} - \bar{C}_W)^2 + 2 \times (\bar{C}_{set3} - \bar{C}_W)^2}{7} \quad (9)$$

$$STD = \begin{cases} |\sigma| & Non-grouped \\ |\sigma_w| & Weighted \end{cases} \quad (10)$$

Tables and plots

Table 2 provides all results of the LDH technique described in Lossless data hiding for privacy: methods and measures section for "GPS_MAP" data. Table 3 provides the same for "Visualization", and Table 4 is for "ECG" data. Table 5 is the aggregated results for all datasets entirely through Eqs. 8–10.

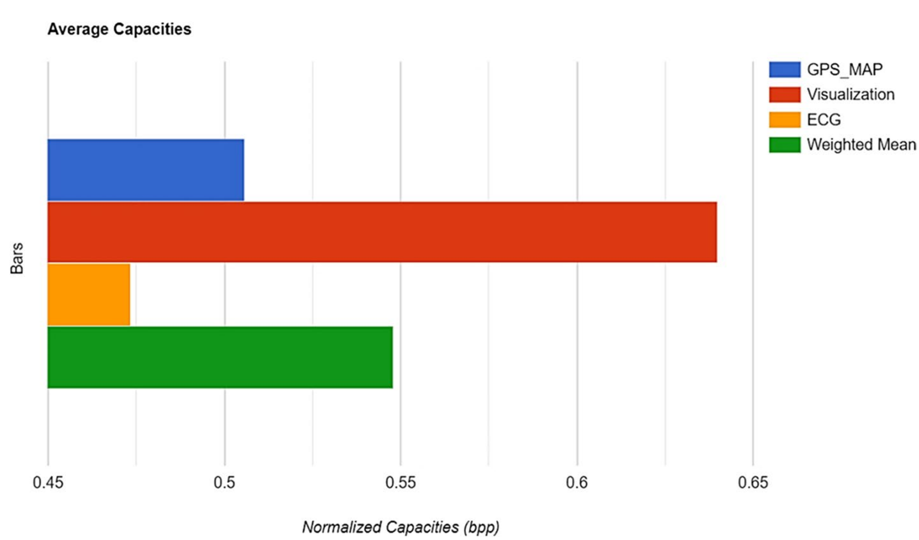

Fig. 6 Results of the average hiding capacity, as normalized-per-pixel, for all datasets

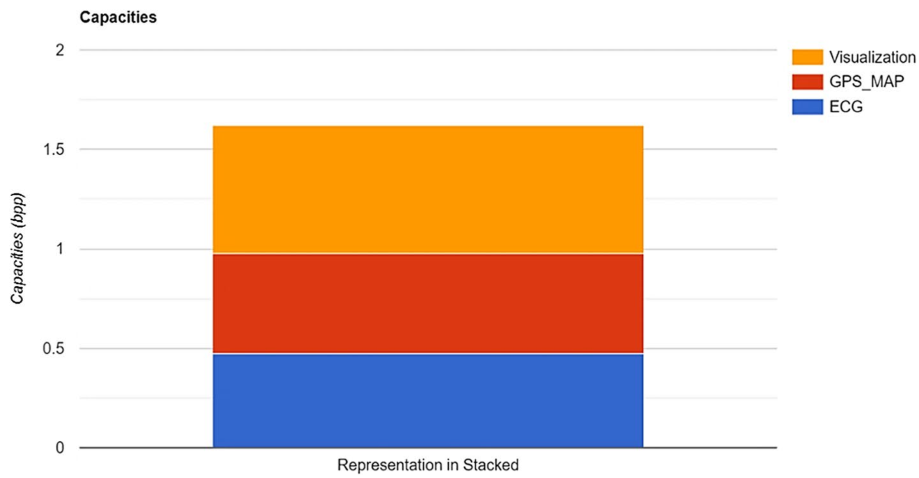

Fig. 7 Stacked bar plot for the three datasets used

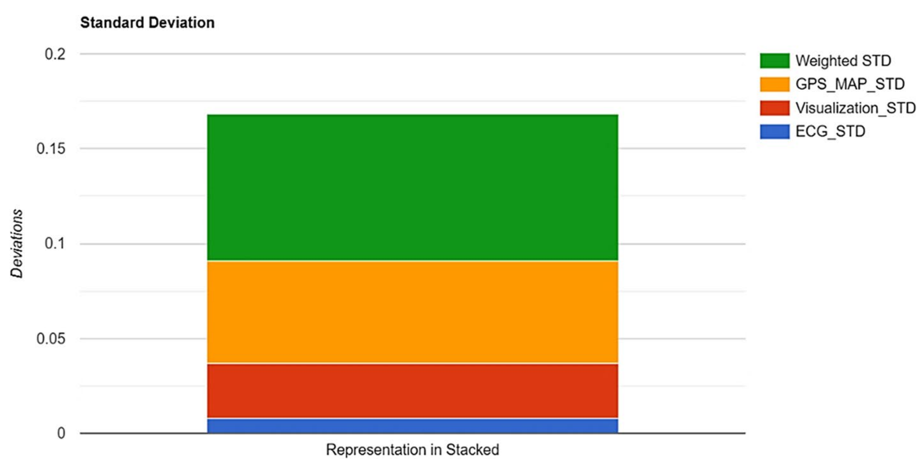

Fig. 8 Results of standard deviation

Also for the tables in order to better understanding, Fig. 6 has illustrated a bar plot for all datasets along with one bar for the weighted mean, Dataset_2 and Dataset_3 have recorded the best and worst hiding performance, respectively. Figure 7 is the stacked form of Fig. 6 after removing the weighted mean.

Figure 8 is showing the stacked bar for the measured standard deviation. It is obvious that the highest amount is for weighted standard division that is computed across all datasets, and it is natural. Among the 3 datasets used, Dataset_1 has obtained the worst results and the best is for Dataset_3. In total, Dataset_2 ("Visualization") has reached the best results and its reliability based on standard deviation is acceptable.

Conclusions

A new private visual information sharing architecture based on LDH over the edge-cloud networks was proposed to realize the data privacy in healthcare systems/H-IoT utilizing wearable biosensors of athletes in public sports, mainly in fitness. The proposed system has considered safe policies based on interconnectivity to keep the athletes' life, and in addition to keep their entity and personal information private in the supporting medical infrastructures to prevent any abuse. The results based on various types of biodata have shown that many lacks still exist in order to develop better data hiding techniques for some health information, here for the ECG sensors. As a suggestion for future research, proposing efficient LDH techniques for a variety of biosensors' data is recommended.

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Authors' contributions
P. L. prepared the main manuscript text and tests; D. S. initially reviewed the manuscript; B.Z. and X.L. provided their technical support in final checking.

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Availability of data and materials
The first dataset: aerial images indicating the direction maps based GPS and vision systems; The second dataset: visualized information recorded by wearable biosensors for heart rate and move; The third dataset: a modern case of ECG reports from Samsung smart watches;

Declarations

Ethics approval and consent to participate
N/A.

Competing interests
The authors declare no competing interests.

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