Artificial Sensitive Skin for Robotics Based on Electrical Impedance Tomography

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Electrical impedance tomography (EIT) is a noninvasive measurement technique that estimates the internal resistivity distribution based on the boundary voltage–current data measured from the surface of the conductor. If a thin stretchable soft material with a certain piezoresistive property is used as the electrical conductor, EIT has the ability to reconstruct the position where the resistivity changes due to the inside pressure contact, so that a large-scale artificial sensitive skin is provided for robotics. First, the different conduction principles and material types of artificial sensitive skins are discussed, which is next followed by the different driving modes and image reconstruction techniques. Then, details on how EIT is used for robotic skin applications are described. Finally, the development trends and future potentials of EIT-based robotic skins are expounded.

1. Introduction

Human–robot interaction (HRI) becomes a research hotspot in the field of robotics in the past 10 years, focusing on shortening the distance between humans and robots.[1,2] Although the research results of HRI have increased significantly, mainly in the field of the audiovisual communication, the tactile field has been seriously ignored.[3] In the social interaction between humans and robots, to interact safely, naturally and intuitively with humans, robots need to have the ability to extract important information from the tactile stimuli. This can be achieved by using the artificial sensitive skins.[4]

In robotics, an artificial sensitive skin is generally composed of a number of, dexterous, reproducible sensors. Artificial skins not only measure a series of physical phenomena such as pressure, vibration, and temperature but also cover the surface of various complex robots.[5–8] In general, many sensors are distributed on artificial skins, but few on the hands and fingers.[9]

The sensors are capable of detecting a variety of information, which are lightweight, rugged, stable, and reproducible.[10] In some cases, multilayer heterogeneous sensors are used more to mimic the function of the human skin.[11] The artificial sensitive skins with the superior ductility and sensitive sensing cover the surface of various robots for a variety of sensing tasks.[12] In general, the artificial sensitive skins are simple, low-cost, reproducible, scalable, and durable. At present, flexible artificial skin composed of multiple sensing units is most widely used. However, the array sensors composed of a large number of sensing units and circuits make the manufacturing process complex and expensive.[13] Therefore, simplifying the structure and reducing the manufacturing cost become a key problem in the development of artificial sensitive skins.

Electrical impedance tomography (EIT) is a noninvasive measurement technique that reconstructs tissue images in vivo with the resistivity distribution of the human body.[14] The essence of EIT is to inject the known current and measure the voltage value to reconstruct the impedance distribution according to a certain method.[15] If the applicable object of EIT is changed from the human body to the sensitive material, the position of the resistance changes due to the external force is reconstructed.[16] EIT is applied to artificial sensitive skins, which not only simplifies the complex structure of sensors but also effectively reduces the manufacturing cost.

As a noninvasive technique to infer the external conductive properties, EIT was first practiced in medical imaging.[17] The first EIT-based lung image was generated by measuring the potential difference on the human chest. The EIT technology is used in many fields due to its unique advantages, such as the Earth exploration,[18–20] industrial applications,[21–23] biomedical imaging,[24–26] and robotic applications based on artificial sensitive skins in recent years.[27–30]

As the EIT-based artificial skin is made of a single material, the calibration process is simple, that is, only one sensor element needs to be calibrated. As opposed to the multiple discrete sensors interconnected in an array configuration, this artificial skin provides the continuous inductive measurements.[31] Because the response of the system depends on the local resistivity changes, materials sensitive to different types of stimuli (temperature) are used to sense other types of stimuli (pressure). Therefore, an EIT-based artificial sensitive skin has the potential...
to solve the problem of the large-scale tactile sensing for robots, which is safe, low-cost, and easy to manufacture.

Following the Introduction section, Section 2 gives a general overview of the different conduction principles and material types of artificial sensitive skins. Section 3 then introduces the different driving modes and image reconstruction techniques in artificial sensitive skins; Details on robotic applications of the large-scale skin-like sensors based on EIT touch sensing are presented in Section 4, which is followed by the development trends and future potentials of EIT-based robotic skins in Section 5.

2. Artificial Sensitive Skins for Robotics

Many skin prototypes have been created in robotics since the introduction of artificial sensitive skins.[11] These prototypes are generally considered to be composed of discrete sensors connected individually or in an array configuration.[11] These sensors with the touch recognition are capable of measuring pressure, vibration, and temperature.[12]

In robotics, many different techniques are used to create tactile sensors that mimic and transcend the subtle pressure-sensing properties of natural skins.[13] A variety of sensing technologies are derived from the exploration of different conduction principles and materials, such as capacitive,[14,35] piezoresistive,[16–39] optical,[40,41] piezoelectric,[42,43] magnetic,[44,45] multicomponent,[46–49] and EIT.[27,48,49] In general, different types of multilayer sensors are used to mimic the sensing capabilities of human skins.[13] Table 1 summarizes various tactile sensors based on different principles, and similar tables are found in the articles.[41,50]

Conductive materials need to be reasonably selected and designed to pursue the high-sensing performance. Table 2 summarizes the characteristics of the various types of structural materials for the tactile sensors, and a similar table is found in the article.[51]

Capacitive tactile sensors are made from a variety of materials with good mechanical properties. Polysilicon has become one of the main material types of capacitive touch sensors.[92,53] Polymer materials, typically polydimethylsiloxane (PDMS) and SU-8 have become more and more popular.[54–56] These polymeric materials have acceptable chemical stability and flexibility. Polymeric materials open up the field of flexible capacitive sensors, which are used in the dielectric interlayers, movable sensing plates, and 3D contact accelerators.[55,57,58]

Piezoresistive tactile sensors require variable electrical resistivity and good mechanical resilience, most of which are common physical properties of metals, semiconductors, and polymeric materials. In early years, resistive tactile sensors have been made from the monocristalline silicon and polycristalline silicon.[59–61] In recent years, research has extensively demonstrated piezoresistive properties in carbon nanomaterials such as multiwalled carbon nanotubes (MWCNTs) and graphene.[62–64] In addition, other supporting polymers are also commonly used for carbon materials. Typical examples include polystyrene (PS), polyurethane (PU), and PDMS.[57,62–64]

Optical waveguide materials are key materials for optical tactile sensors. Dating back to 1970s, composite such as ZnCl₂ glass has been proposed as fiber materials.[65] Silica materials are very good options for single-mode optical fibers.[66] Conventional polymer fibers include poly(methyl-methacrylate) (PMMA), PS, polycarbonate (PC), PU, and epoxies.[67] Newly explored optical polymers include the following: deuterated and halogenated polyacrylates, fluorinated polyimides, benzocyclobutene, and perfluorovinyl ether copolymers.[67] Materials for supportive structures include acrylic polymers, PDMS, and nitinol.[68–70] Materials for optical tactile sensors have to fulfill certain optical transparency and elasticity requirements.

Piezoelectric tactile sensors rely on piezoelectric properties, which have a narrow selection of available materials. For rigid structures, common materials are the quartz, zinc oxide, and lead zirconate titanate (PZT), whereas flexible sensors have been made from zinc oxide-based nanomaterials.[71–74] Recently, polyvinylidene fluoride (PVDF) is a popular choice for flexible...
Recent research indicates that cellulosic materials with piezoelectric properties will be a novel material for the fabrication of flexible piezoelectric tactile sensors. Over other technologies, EIT has attracted the attention of many researchers at home and abroad. In 2007, the robotic applications of EIT-based sensitive skins are first proposed by Kato et al. and Nagakubo et al. The electrodes are placed on the boundary of the conductive materials in response to the local resistivity changes. As most of the sensitive areas of the EIT-based artificial skins are made of a homogeneous, thin, stretchable, and flexible material without any or very limited internal wires, flexible sensitive skins that are large, flexible, and stretchable are possibly created.

Although EIT-based sensitive sensors overcome the shortcomings of most conventional sensing methods, they have the poor spatial resolution, low temporal resolution, and limited ability to distinguish between the pressure strength and contact area. Therefore, EIT-based artificial skins are not suitable for applications that require image reconstruction with high-frequency temporal resolution and millimeter-level spatial resolution. However, EIT is applicable to a variety of applications about the real-time distributed pressure monitoring, including the gait detection in biomechanics. In robotics, EIT-based artificial skins are suitable for the touch sensing, where the spatial resolution of 10–40 mm and reconstruction frequency up to 45 Hz are sufficient. The following sections describe the driving modes and image-reconstruction techniques for the touch sensing, as well as a variety of robotic applications for large-scale skin-like sensors based on EIT.

### 3. EIT for Artificial Sensitive Skins

EIT is a noninvasive imaging technique that estimates the distribution of internal resistivity by measuring only at the conductor boundary (as shown in Figure 1). If the local resistivity inside the conductor changes, the current distribution also changes, and the induced current and potential at the boundary change correspondingly.

**Table 1. Summary of various touch sensing technologies.**

| Type                  | Sensing principle               | Advantages                                           | Disadvantages                                             |
|-----------------------|---------------------------------|------------------------------------------------------|-----------------------------------------------------------|
| Capacitive[34,35]     | Capacitive change               | High sensitivity, good spatial resolution, large     | Stray capacitance, noise sensitivity, electronic         |
|                       |                                 | dynamic range                                        | measurement complexity                                     |
| Piezoresistive[36–39] | Piezoresistive change           | High spatial resolution, high scan rate, low cost.   | Low repeatability, large hysteresis, high power           |
| Optical[40,41]        | Light intensity or spectral change | Large sensitivity range, high reliability, good spatial resolution, no electromagnetic interference, fast response. | Large size, narrow adaptability and high power consumption. |
| Piezoelectric[42,43]  | Stress (strain) polarization    | High frequency response, high sensitivity, high dynamic performance. | Poor spatial resolution, only dynamic perception, susceptible to temperature changes. |
| Magnetic[44,45]       | Magnetic coupling               | Linear output, high dynamic performance.             | Moving parts, low spatial resolution, large size, susceptible to noise. |
| Multi-component sensors[46,47] | Multi-parameter coupling | Overcoming certain limitations by combining internal parameters, discrete components. | High assembly cost. |
| EIT[77,48,49]         | Electrical impedance change     | High versatility, low cost, low power consumption, no mechanical parts, no internal wiring, high sensitivity range. | Poor spatial resolution, low time frequency. |

**Table 2. Summary of various structural material types.**

| Material types       | Patterning | Properties                                           |
|----------------------|------------|------------------------------------------------------|
|                      | Deposit    | Etch                                                 |
| Silicic              | High-temperature, high-vacuum, low-pressure, complex equipment. | High-risk chemicals, complex equipment.               |
|                      |            |                                                      | Good mechanical properties, adjustable conductivity, good thermal conductivity, good optical properties, high chemical stability. |
| Metallic             | Flexible temperature, flexible vacuum, medium pressure, medium complex equipment. | Flexible etching methods, simple equipment.           | Good conductivity, good thermal conductivity, medium chemical stability. |
| Polymeric            | Low-temperature, low-vacuum, high-pressure, simple equipment. | Safety chemicals, high pressure.                     | Medium and low mechanical properties, thermal insulation, highly flexible functionality, good optical properties, low chemical stability, easy oxidation. |

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**Figure 1.** Principles of EIT. The alternating current signal (I(ω)) is injected through two red electrodes, and the induced potential (V(ω)) is measured on the other two blue electrodes. Reproduced with permission.[86]
Table 3. Summary of different EIT driving modes.

| Driving modes             | Advantages                                      | Disadvantages                                                                 |
|---------------------------|-------------------------------------------------|--------------------------------------------------------------------------------|
| Adjacent method[87,88]    | Good edge sensitivity, more current injection.  | Poor mid-mind sensitivity, susceptible to boundary shape, electrode position, measurement error, and electrode noise interference. |
| Opposite method[89,90]    | Good overall sensitivity, uniform current distribution. | Poor edge sensitivity, low current injection.                                  |
| Trigonometric method[91]  | Good center sensitivity, high current injection. | Each independent current driver, susceptible to unknown contact impedance.       |

Figure 2. Different EIT driving modes, a) adjacent current driving mode, b) opposite current driving mode, c) trigonometric driving mode. Reproduced with permission.[87] Copyright 2013, BEIESP.
and EIT is used to measure these changes. If the body is made of a thin, stretchable, and flexible material, the artificial sensitive skin is created for the touch sensing.

The current is injected by a pair of electrodes in contact with the surface to measure the voltage difference of the object. Table 3 summarizes the driving modes of various current injections and voltage measurements.

The adjacent driving method is the most common current driving mode (as shown in Figure 2a).[87,88] The opposite driving method is another driving mode for the impedance measurement (as shown in Figure 2b).[89,90] In the aforementioned methods, a current is injected with a pair of electrodes, and the voltage difference is measured without the current electrodes.

Differently, the trigonometric driving method injects the current into all electrodes and measures the voltage across all electrodes (as shown in Figure 2c).[91] However, each electrode requires a separate current driver, which is impractical in robotic applications. Also, the unknown contact impedance has a large impact on the image reconstruction.

The image reconstruction of the EIT technique is a process to find the resistivity distribution inside the conductor when a set of injection currents and generated voltages are known,[92] which is a nonlinear inverse problem. The main difficulty is that the small changes in the boundary data may lead to large changes in the reconstructed image.[93]

In recent years, many researchers have worked on different artificial intelligence and evolutionary algorithms to solve the EIT inverse problem.[94] These nonlinear methods will provide good results if the assumptions of reconstruction problems are simplified. The neural network (NN) is used to solve the EIT inverse problem. The advantage of NN is that the inverse solution of the matrix is taken directly from the finite element method (FEM), and the signal–noise ratio (SNR) is obtained without any initial assumption and calculation. Another possible

| Classification        | Reference         | Algorithm                  | Remarks                                                                 |
|-----------------------|-------------------|----------------------------|------------------------------------------------------------------------|
| Improved algorithms   | Ying et al. (2003) | Differential evolution     | Differential evolution algorithm for the real brain image reconstruction. |
|                       | Trigo et al. (2004)| Extended Kalman filter     | Extended Kalman filter for estimating the impedance distribution to resolve the image reconstruction. |
|                       | He et al. (2006)  | Active filter linear back projection | Active filter linear back projection algorithm (LBPA) for the image reconstruction. |
|                       | Liu et al. (2006) | Support vector machine     | Support vector machine instead of LBPA for the image reconstruction.    |
|                       | Jing et al. (2007)| Fletcher Reeves            | Fletcher reeves algorithm transforms ill-posed problems into minimization problems to solve the image reconstruction. |
|                       | Chen et al. (2007)| Landweber Iteration        | Landweber iteration algorithm for the image reconstruction, and Tikhonov regularization instead of LBP algorithm to improve the convergence speed. |
|                       | Chen et al. (2009)| Iterated Tikhonov          | New operators for standard Tikhonov algorithms, increasing computational speed and accuracy. |
|                       | Paulo et al. (2006)| CA                         | CA is used to optimize the minimum reconstruction error problem to improve image reconstruction quality. |
|                       | Grazieli et al. (2007)| HPGA                      | Hybrid parallel genetic algorithm (HPGA) adds a priori information to provide good global minimum search results for the image reconstruction. |
|                       | Xiao et al. (2011)| IGA                        | Improved genetic algorithm (IGA) is used for the EIT forward problem.   |
|                       | Sun et al. (2010) | APSO                       | Adaptive particle swarm optimization (APSO) is used to adjust the gray border of the reconstructed image. |
|                       | Zhang et al. (2013)| MPSO                       | Modified particle swarm optimization (MPSO) is used to reconstruct the impedance distribution to find the target. |
|                       | Liu et al. (2014) | PSO-GNA                    | PSO optimizes impedance distribution, Gauss-Newton algorithm (GNA) solves the image reconstruction problem. |
|                       | Wang et al. (2015) | PSO-LBPA                   | PSO is used to optimize LBPA to improve imaging results.               |
|                       | Marashdeh et al. (2006)| Feedforward NN            | Feedforward NN is used to solve forward problems, using experimental data for network training. |
|                       | Zhang et al. (2008) | WNN                        | Wavelet neural network (WNN) minimizes the dimensionality of the input vectors and speeding up the learning process. |
|                       | Zhang et al. (2009) | Algebraic NN               | Algebraic NN converts the image reconstruction to solve linear problems with good convergence and small errors. |
|                       | Raiwa et al. (2014) | RBFNN                      | Radial basis function neural network (RBFNN) is trained by analog voltage measurements. |
|                       | Xin et al. (2016) | BPNN                       | Back propagation neural network (BPNN) is used for the image reconstruction through the adaptive learning. |
|                       | Russo et al. (2017)| ANN                        | Finite element data is used to train the ANN to detect target touch information. |
|                       | Hrabuska et al. (2018) | HNN                      | Hopfield neural network (HNN) enables higher quality image reconstruction than GNA. |
|                       | Duan et al. (2019) | DL-NN                      | Deep learning (DL) is used to train NN to dynamically sense target position. |
way is to treat the EIT inverse problem as an optimization problem, which is solved by different evolutionary algorithms, such as the genetic algorithm (GA) and particle swarm optimization (PSO). These evolutionary algorithms work by reducing the root-mean-square errors between the analog and measured potentials. Table 4 summarizes how different authors use these different algorithms to solve the EIT image reconstruction, such as improved algorithms, evolutionary algorithms, and intelligent algorithms.[29,95–115]

No matter which kind of imaging technologies, it comes down to a problem in mathematics, that is, how to determine the projection of the 2D distribution in a 1D space according to a function of the 2D spatial distribution.[116] This so-called dimensionality difficulty makes any kind of imaging technologies to encounter the computational instability and error sensitivity.[117] No matter which imaging technology, to some extent, the same basic approach is followed. If the problem is nonlinear, then the problem is linearized; if the problem is ill-posed, then a priori information is added to find the nearby moderate problem by the regularization; if the linear approximation is not correct, the error is minimized by the iterative solution.[118]

4. EIT-Based Skin Applications

The main component of EIT-based artificial skins is a variable resistivity material for manufacturing.[86] The ideal material has the light weight, low cost, continuous uniform conductivity, and no hysteresis. This material undergoes large, linear, and local resistivity changes in response to the external stimuli (touch and pressure). Moreover, the resistivity of this material does not change due to the bending, stretching, or temperature changes. To find materials that meet these criteria, many experiments have been studied. Table 5 summarizes the current EIT-based artificial skins of various materials.

For the first time, Kato et al. develops the EIT-based single-layer pressure-sensitive skin by mixing rubber with conductive carbon particles.[81] However, due to the nature of the rubber, the skin is elastic but not stretchable. The conductive rubber has the high hysteresis, in which only a small change in resistivity is fed back in response to the external pressure.[112] Mukai et al. uses this new conductive rubber as a sensitive material and reconstructs the force image based on EIT.[119]

The tactile sensor is simplified in the unit structure and applied to the rehabilitation robot (as shown in Figure 3), so that the robot has the ability to transfer the human body between the hospital bed and the wheelchair.

Cheng et al. also studies the conductive rubber with a good stable piezoresistive property.[12] The rubber body is composed of PDMS and MWCNTs. The resistance value is significantly reduced as the applied pressure increases. The feasibility of the EIT system is verified by imaging experiments on multiple targets (as shown in Figure 4). However, the EIT system is only suitable for the 2D shape-formed imaging, and the imaging accuracy is poor.

Differently, Nagakubo et al. studies the conductive fabric by spraying the conductive waterborne carbon coatings on the surface of ordinary fabrics.[84] Based on this material, the EIT-based single-layer high-stretch pressure-sensitive skin (as shown in Figure 5) is made to cover the 3D portion of the mannequin, such as the face or elbow of the model. The surface resistivity of the

### Table 5. Summary of EIT-based artificial skins of different materials.

| Layers                  | Materials                                                                 | Feature                                                                 | Publication                  |
|-------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------|-----------------------------|
| Single-layer conductive rubber | Rubber and conductive carbon particles are mixed.                       | Good elasticity, low stretchability, high hysteresis, poor piezoresistive. | Kato et al. (2007)[81]      |
|                         | PDMS and MWCNTs are mixed.                                                | Low stretchability, good piezoresistive, only suitable for 2D shape-formed imaging. | Mukai et al. (2010)[119]   |
| Single-layer conductive fabric | Spraying conductive water-based carbon coated on the surface of the fabric. | High stretchability, low hysteresis, susceptible to tensile changes.     | Nagakubo et al. (2007)[81]  |
|                         | Medical-grade silver-plated nylon fabric (Less EMF Inc.).                 | High conductivity, high stretchability, low hysteresis, biaxial stretching. | Soleimani et al. (2012)[84] |
|                         | Non-woven microfiber fabric (Eeonyx Corp.).                               | Low stretchability, low hysteresis, not susceptible to tensile changes.   | Yang et al. (2013)[120]     |
| Two-layers conductive fabric | Elastic fabric coated with conductive polymer (Eeonyx Corp.).             | High stretchability, good piezoresistive, not susceptible to tensile changes, dynamic sensing of the complex pressure touch. | Russo et al. (2017)[129]     |
|                         | The bottom layer is a wavy nylon gauze containing conductive copper sulfide, and the top layer is a conductive foil containing silver-plated fabric. | Good stretchability, high conductivity, good piezoresistive, not susceptible to tensile changes, covering full-size mannequin arms, machine learning for touch classification. | Duan et al. (2019)[113]     |
| Three-layers conductive fabric | The bottom layer is a carbon-coated conductive fabric (Eeonyx Corp.), the second layer is a thin silver-plated fabric (Less EMF Inc.), and the top layer is a soft suede fabric. | Good stretchability, high conductivity, high piezoresistive, not susceptible to tensile changes, covering full-size mannequin arms, machine learning for touch classification. | Tawil et al. (2011)[120]    |
| Four-layers conductive fabric | The bottom and top layers are highly conductive silver plated nylon fabric, the second layer is an elastic fabric coated with a conductive polymer (Eeonyx Corp.), and the third layer is a non-conductive honeycomb grid fabric. | Good stretchability, high conductivity, good piezoresistive, high sensitivity, lightweight, flexible, and breathable wearable tactile glove. | Gereon et al. (2015)[121]   |
Figure 3. Low-stretch single-layer rubber EIT-based artificial skin: a) the single-layer artificial skin is placed on the surface of the robot arm without the surface coverage; b) the surface of the artificial skin is covered with a layer of the nonconductive material. Reproduced with permission.\textsuperscript{119} Copyright 2010, IEEE.

Figure 4. Low-stretch single-layer rubber EIT-based artificial skin: a) imaging reconstruction results for one target, b) the weight of the left target in the two targets is two times the right target, c) the weight of each target in the three targets is the same. Reproduced with permission.\textsuperscript{32} Copyright 2016, Chinese Journal of Sensors & Actuators.

Figure 5. High-stretch single-layer fabric EIT-based artificial skin: a) the square artificial skin is placed on the complex 3D surface, b) the pressure is exerted on the artificial skin, c) the reconstructed resistivity changes are represented in two dimensions due to the applied pressure. Reproduced with permission.\textsuperscript{48} Copyright 2007, IEEE.
material changes as it is stretched in the plane or compressed to the plane of the fabric. The conductive fabric not only has greater stretchability than the conductive rubber but also has less hysteresis. However, the large resistivity changes due to the tensile changes are a significant disadvantage.

Yao et al. also report similar methods using single-layer conductive fabric for the deformation of the surface.\textsuperscript{84,120} Yao and Soleimani use a high-stretch ($\sigma \approx 1000 \text{ mS sq}^{-1}$) medical-grade silver-plated nylon fabric (from Less EMF Inc.).\textsuperscript{120} The conductive fabric is stretched in two directions (as shown in Figure 6a). Yao and Yang et al. use a nonwoven microfiber conductive fabric (from Eeonyx Corp.) with the low stretch ($\sigma \approx 0.667 \text{ mS sq}^{-1}$), low hysteresis, and small deformation.\textsuperscript{84} The conductive fabric measures the pressure distribution of the human foot using EIT to test the resistivity changes of the fabric (as shown in Figure 6b). However, the closer to the center area, the lower the sensitivity and the less clear the reconstructed image.

Similarly, the single-layer elastic fabric coated with the conductive polymer (from Eeonyx Corp.) is also used.\textsuperscript{29,115} However, more emphasis is placed on combining the artificial intelligence with EIT for better image reconstruction. Russo et al. uses the artificial neural network (ANN) to solve the static image-reconstruction problems (as shown in Figure 7a).\textsuperscript{29} ANN is trained to detect the contact position and size of the object based on the size data of different targets. However, how to choose the appropriate region of interest (ROI) threshold for different targets is a major drawback. Duan et al. combines the deep learning with the EIT dynamic imaging (as shown in Figure 7b).\textsuperscript{115} NN is trained to verify feasibility in multipoint dynamic touch-sensing experiments based on independently collected data sets. NN has the strong adaptability and learning ability, which improves the imaging resolution and effectively reduces the error information.

Alirezaei et al. and Tawil et al. focus on the combination of different multilayer materials, such as conductive yarns and fabrics.\textsuperscript{88,90} These multilayer composites are designed to improve the pressure response and minimize the resistivity changes due to stretching. Alirezaei et al. uses two different types of stretch-insensitive conductive structures: 1) the high-stretch wavy conductive gauze and 2) the low-resistance conductive fabric.\textsuperscript{88} The bottom layer is the wavy nylon gauze containing the conductive copper sulfide, and the top layer is the conductive foil containing the silver-plated fabric (as shown in Figure 8). By using wavy yarns, the total length of the yarn remains constant as the fabric is stretched. Therefore, the resistivity changes caused by stretching are eliminated and insensitive to stretching. However, due to the nonlinear changes in the contact area, the resistivity with pressure changes nonlinearly. The feasibility for detecting tactile gestures (pinch, push, and tweezer) on complex surfaces is tested. Moreover, due to the limitations in available materials and manufacturing techniques, the specifications of the conductive sheets are rough, the spatial resolution of the

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![Figure 6. Single-layer EIT-based artificial skin: a) a circular tactile sensor is made of a high-stretch conductive nylon fabric (left); the resistivity changes of multiple points are reconstructed in response to the pressure or stretching (right), b) A square tactile sensor is made of a microfiber conductive fabric (left); the resistivity changes of the foot are reconstructed in response to the pressure (right). a) Reproduced with permission.\textsuperscript{1120} Copyright 2012, Emerald Publishing Limited. b) Reproduced with permission.\textsuperscript{84} Copyright 2013, Hindawi.](image-url)
Conductive screens is poor, and the nonstretchable electrode lines also limit the possibility of increasing the sensors, which all require further improvement.

Tawil et al. uses a similar method, but the difference is that the bottom layer used two layers of fabric instead of one layer. The bottom layer is the carbon-containing conductive fabric (from Eeonyx Corp.). The surface resistivity ($\sigma \approx 12.5 \text{ mS sq}^{-1}$) changes with stretching and the measuring electrode is fixed on the layer. The second layer is the thin, high-stretch ($\sigma \approx 660 \text{ mS sq}^{-1}$), silver-plated fabric (from Less EMF Inc.). The contact area between the two layers reduces the resistivity changes caused by stretching to some extent. To allow the detection of multiple pressure points, the second layer is made of unconnected discrete square conductive fabrics, which also reduces the probability of the current loss. To make the artificial skin look more natural, more beautiful and more comfortable, the top layer is covered with
Figure 9. Three-layers conductive fabric EIT-based artificial skin: a) the 3D model diagram of the irregular-shape artificial skin, b) artificial skins placed on the 3D surface of the artificial arm, c) resistivity changes due to pressure applied to the arm. Reproduced with permission. Copyright 2011, IEEE.

Figure 10. Four-layers conductive fabric EIT-based artificial skin: a) the construction of the flexible tactile sensor with four fabric layers, left—the photograph of the assembly, right—the schematic representation, b) the wearable data glove with 54 tactile cells and embedded data acquisition electronics. Reproduced with permission. Copyright 2015, Elsevier.
the soft suede fabric (as shown in Figure 9). This multilayer fabric artificial skin is thin, flexible and stretchable, which covers the full-size mannequin arm. Machine-learning algorithms are used to automatically classify nine different tactile gestures and twelve discrete social messages that humans typically pass by touch.

Büsch er et al. design the novel flexible tactile sensor using four layers of different stretchable knit fabrics.\[12\] The bottom and top layers are composed of the highly conductive silver-plated elastic nylon fabric (78% polyamide fiber (nylon) and 22% elastomer). These outer layers form the low-impedance (<2 Ω sq\(^{-1}\)) electrodes that sink current into or out of the sensor with the minimal loss. The second layer consists of the elastic fabric coated with the conductive polymer (72% nylon and 28% spandex, from Eeonyx Corp.). This layer is the varistor layer, where the resistivity changes under the mechanical pressure and are measured on the outer electrodes. The volume resistivity (≈20 kΩ) is more suitable. The third layer is the single-layer honeycomb nonconductive mesh fabric. With this extra mesh layer, the gap is introduced between the electrode and the piezoresistive layer. As the force required to reduce the gap is small, the sensor is sensitive to subtle forces. The high resistance at no load reduces the energy loss, especially in large-scale applications. The sensitivity depends on the thickness and size of the mesh layer. The thinner the layer, the larger the hole, the better the sensitivity. Based on these multilayer composites, the wearable tactile glove with 54 haptic units and embedded data acquisition electronics is constructed (as shown in Figure 10). The tactile glove measures the pressure on the entire palm surface and all fingers, which is lightweight, flexible, and breathable.

In these methods, the electrodes are located on the edges of the conductive materials, such as rubbers, foams, or fabrics. When the current is injected through the electrodes, the pressure distribution is converted on the surface into the impedance distribution, which is then measured using EIT. Because these sensors are made of flexible materials without any or very limited internal wires, sensitive skins of any size and shape are created to detect the pressure such as swiping, squeezing, and gripping.

5. Conclusion

This article reviews the research status of robotic applications of large-scale skin-like tactile sensors based on EIT. The focuses are on the transmission principles of artificial skins, EIT-based driving modes, image reconstruction technologies, material types, and skin manufacturing technologies. Due to many advantages of EIT, EIT-based artificial sensitive skins are expected to solve the large-scale tactile sensing in robotics. At present, due to the limitations (the lower temporal resolution and poor spatial resolution), the EIT-based artificial skins are not fully integrated to cover multiple structural parts of 3D robots, which requires a lot of research and development. Future work considers developing new stretchable flexible skin material with the linear machine–electric behavior. The machine–electric behavior requires the consideration of ideal properties of the material and new approaches of the image reconstruction. The ideal properties of the material are light weight, low cost, continuous uniform conductivity, and no hysteresis. The new approaches of image reconstruction incorporate more information about materials and robot behaviors. Different artificial intelligence algorithms are combined to improve image reconstruction quality and allow better differentiation of the contact area and pressure strength. Therefore, many studies are still needed to develop more suitable EIT-based skin materials, and to combine these materials with the existing hardware and software to address the challenges in the sensor design, instrument development, and image reconstruction.

In the near future, with the rapid development of EIT, the EIT-based artificial sensitive skin is a kind of thin, stretchable, and soft artificial skin. The artificial skin with only a small number of electrodes and wires are cut into any shape and applied to cover any structure surface of 3D robots. Therefore, the EIT-based artificial sensitive skins could be widely used in robotics, biology, medical, and industrial fields.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

artificial sensitive skin, electrical impedance tomography, human–robot interactions, robotics, tactile sensors

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