Simulation Techniques and Prosthetic Approach Towards Biologically Efficient Artificial Sense Organs- An Overview

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Abstract. An overview of the applications of control theory to prosthetic sense organs including the senses of vision, taste and odor is being presented in this paper. Simulation aspect nowadays has been the centre of research in the field of prosthesis. There have been various successful applications of prosthetic organs, in case of natural biological organs dis-functioning patients. Simulation aspects and control modeling are indispensable for knowing system performance, and to generate an original approach of artificial organs. This overview focuses mainly on control techniques, by far a theoretical overview and fusion of artificial sense organs trying to mimic the efficacies of biologically active sensory organs.

Keywords: virtual reality, prosthetic vision, artificial electronic tongue, prosthetic nose, artificial neural network, vibrotactile sensing.

1. Introduction. One of the faculties by which the qualities of the external environment are appreciated that is sight, hearing, smell, taste or touch is called human sense. A collection of specialized cells (receptors) connected to the nervous system, that is capable of responding to a particular stimulus from outside or inside the body are the sense organs. As the lens helps a camera to track any object, similarly eye acts as an organ for human vision. A sensor tells us the identity of any object by sensing it; similarly nose acts as our body sensor, helping us to identify anything with its odor. Similarly tongue (the organ of taste) acts as a clinical sensor, and ear the organ of hearing works just as a microphone. All the human impulses coming from various sense organs, finally travels to the brain through the nervous system. Thus the brain acts as a control centre for different human actions. In this paper, a brief discussion is furnished on three artificial human sense organ control and modeling, i.e. eye, nose and tongue.

2. Visual Acuity and Virtual reality leading towards prosthetic vision: For centuries, restoration of proper eyesight to the blind has come to be considered nothing less than a miracle. Today, the resources are unlimited. Extensive researches and studies conducted today bear the promise of making restitution of sight a real medicinal achievement, tomorrow. Affordable for the common man, restoring eyesight would no longer come with the uncertainty of success. Pursuing that goal, leading researchers from the fields of ophthalmology, biology and computer engineering have united their efforts. This special report on bio-electronic vision, would reveal how for this field has been successfully explored and how much it is yet to be accomplished. Proper reception of prosthetic vision banks heavily upon the ability of the recipients in forming
functional information from such vision. Several of the aforesaid critical factors were tested in a visual acuity study under virtual-reality replication of prosthetic vision using the Landolt C optotype. Fifteen subjects with normal sight were examined for many sessions. With regression models, the prime learning aspects were tested [1]. Learning was greatly directed toward a vital range of optotype sizes, and the subjects generally lacked ability in identification of the closed optotype (a Landolt C without any gap, creating a closed annulus). Preparation for implant receptors should aim these vital sizes as well as the closed optotype to eliminate the limitations of visual comprehension. Though no firm evidence can be provided that image processing influenced overall learning, personal preferences of the subjects varied widely. Several reports of successful clinical trials of visual neuro prosthesis prototypes indicate towards a major achievement made in the restoration of vision to the blind. The primary objective is to substitute the visual neural signaling with artificial signals reproduced by electrical stimulations. The success of the trials lies in eliciting spots of light, also termed as phosphenes, in the visual space, in correspondence to the application of electric current [2-9]. Drawing inspirations from these, many investigators have further researched simulated prosthetic vision with subjects having normal eyesight. Attempts are being made to explore more the extent of its capabilities and thereby gain more insight. The performance results received on the simulated prosthetic vision on visual acuity, object identification, hand-eye synchronization, fast reading ability [10–14], maze navigation [15] and object tracking [16][17], are optimistic enough that boost experimental activities in future. Learning is the core of this paper. Quite unfortunately, and also surprisingly, learning has gone largely unnoticed in the literature of prosthetic vision. Plasticity of the cortex aids learning to a large extent. The phenomenal success with the cochlear replacements for the hearing impaired is based upon plastic alterations in the auditory cortex [18]. Learning of visual assignments and the cortical systems underlying such procedures have also been well researched, revealing a visual cortex [19–21] with high adaptability. Furthermore, it is also established that the visual cortex of blind subject becomes accustomed to verbal memory and Braille reading tasks [22]. It is expected that the visual cortex would adapt to the “artificial” neural signals. The same has been illustrated in the auditory cortex of cats [23][24]. These works attempts to look into the learning of prosthetic vision through virtual-reality simulation with human subjects having normal eyesight. Learning based on perseverance is mainly of two types: fast learning which depends on sensory units for executing the task, and slow learning where the cortical neurons and perceptual modules [25][26] are interconnected, thus strengthening the memory of fast learning into a more lasting memory. Since the early time the development in monosyllabic word identification by cochlear embedded patients can be assigned to speech recognition, as stated in[27]. Prosthetic vision can be said to be analogous to Uttal’s visual technique [28] and “vontour integration [29], other than the absence of Gabor function in phosphene elements as studied in visual psychophysics [30]. Its just a matter of time now after which guide dogs, and walking canes formerly used by blind people will be of no use to them as stated by Dobelle [31]. Proving him right, Humayun et all [32][33] and Veraart et all [34] showed that suitable electrical current wave form if passed through undamaged part of human eye can evoke rounded light
spots called phosphenes. Many earlier works on prosthetic vision such as visual sharpness and speed of reading shown by Cha et al. [35-37], Hayes et al. [38] and Thompson et al. [39] came up with ideas of added object recognition and facial recognition respectively gave us a vivid idea of prosthetic vision technique. The number and density of phosphenes [40] gave us a new edge towards prosthetic vision analysis. Contracting information from every image frame in a limited phosphenes number with the help of an algorithm was stated by Hallum et al. [41], which described the task of tracing an object under simulated prosthetic vision. Spatial frequency component of Landolt ring and E-optotype discussed by Bondarko and Denilova [42] stated that lower frequency component is almost half of higher frequency component.

3. **Fuzzy neural network germinating Bio-electric prosthetic nose:** The artificial nose concept was around through the years and was developed by various researchers in this field till recent dates. This prosthetic device has been developed to grasp odors, vapors and gases automatically. Generally the constitution of artificial nose requires a sensor system and a pattern recognition system. An order-reactive polymer sensor, generating pattern of resistance make the classification of the odorant stimulus [43]. Also the use of Artificial Neural Network produces proving results in Time Delay Neural Network [44]. However, hybrid application, as the use of Wavelet Analysis, the use of neuro-fuzzy networks and extraction of classification rules of the sensors of the artificial nose help to build this device [45-47]. The optical gas sensors also demand large applications in this prosthetic nose field [48]. The optical technique based on UV-Vis spectroscopy has been described as an efficient tool to obtain the sensing response of these materials to various volatile organic compounds (VOCs) [49][50], by its measurement of the changes in spectra. Computing techniques have been adapted to solve the classification problems, KNN is one of them [51]. From the past several years, development on the hybrid system for odor detection based on the olfactory organs of insects was going on [52][53]. Recordings from 21 individual glomeruli of honeybees have recently been used for the classification of several odors using the technique of principal component analysis (PCA) [54]. Original sensor fusion method on the basis of the opinions of human smell and taste and the measurement data from artificial nose and taste sensors is obtained from [55]. Whether, in the market the commercial uses of electronic noses have already been started [56-58], similar concepts for analysis of liquid is described, but for the tasting sense the terms „electronic tongue” or „taste sensor” have been used [59-62]. To implement the pattern recognition system of artificial nose, studies have been done on the several types of ANN. The models like Multilayer Perceptron (MIPS) with, respectively, back propagation (BP), resilient back propagation (Rprop) and tabu search (TS), and networks with radial basis function (RBF networks) are analyzed [63-68]. This overview paper on artificial nose cannot be flourished without the help of [69-72].

4. **Neural Network acting as an aid for the test receptors of an Electronic Artificial Tongue:** A muscular organ attached to the floor of human mouth, covered by a mucous membrane having minute projections (papillae) on its surface is the Tongue. It helps in manipulation during mastication and swallowing. Other than these, it is the primary organ of taste and also played an
important role in producing speech [73]. Test has mainly five descriptors (salt, sour, sweet, bitter, umami) and for hot and cold [74]. Looking at the importance and usefulness of tongue many researchers aim for the development of sensory system related Electronic Tongue (E Tongue) which will mimic human sensory tongue both in structure and efficiency. An electronic tongue or „taste sensors“ including arrays of ion selective and non-selective electrodes must be capable of detecting any chemical substance. Nowadays chemical/biological sensors for liquid analysis are widely accepted techniques in various research fields [75]. The first concept of the taste of sense was reported fifteen years ago [75][76]. For measuring the metal ions, present in river water, a calcoenide glass electrode based electronic tongue was modeled [76].

Followed by this, an electronic tongue aimed at analysis of beverages comprising of PVC and glass electrodes was introduced [77]. The membrane of electronic tongue comprised of eight kinds of lipid analogues. Based on lipid/polymer coated membrane, a taste sensory or electronic tongue was modeled [78] [79]. A kind of taste sensors are the resonant sensors. For detection of liquid species QCM is used, but the high oscillator damping gives rise to some electronic based requirements [80]. Not only this QCM also helps in miniaturizing the arrays [81] varying the sensitivity. Though the use of FPW (a type of resonant sensor) is known for long time but the first application of electronic tongue came much latter [82] . But with utmost surprise and in contrary with all the electronic tongue models described till now, a completely different idea of electronic tongue came in 1997 [83]. Pulse Voltammetry used E. Tongue [84][85] consisting of six working electrodes of different metals, along with an auxiliary electrode and a reference electrode was then modeled. The voltammograms records were dependent on large amplitude pulse voltammetry (LAPV) [86]. Researchers of various ages were highly tilted towards solving the pattern recognition issue, in case of sense of taste with the help of an Artificial Neural Network (ANN) [87]. Their urge was more stimulated when Kyushu University scholars, Tokyo-Yamafuji came up with a taste transducer, using lipid membranes [88][89]. This group of Kyushu University came up with another prolific idea of multichannel taste sensor [90][91] consisting of eight different lipid membranes that converts the taste strength to electric potential and respond to different types of taste sensations. Electro physiological study on the thin lingual membrane of tongue has proved it to be a highly active transporting tissue and is shown in[92-95]. The reading difference between water readings and red wines in electronic tongue with the help of MLP networks is discussed in another work by Costa De Sousa et al. in 2002. The electro physiological studies of taste receptor cells that remain in cell collection of nearly 100 cells [96] together gives the sensation of salt [97]. Other than this the taste of beer and other food stuffs with the help of electronic sensing of electronic tongue was discussed in [98]. The reading difference between water readings and red wines in electronic tongue with the help of MLP networks was discussed in [99].

5. Sound Source Localization Using Artificial Neural Network leading towards Prosthetic Ear:
The artificial ear concept was around and developed through the years by various scientists and researchers in this field. The comparison and experiment between two promising classification techniques, non-windowed artificial neural networks (ANN) and hidden Markov models (HMM), with an artificial neural network using windowed input is shown in [100]. In spite of the huge use of hearing aids, it is responsible for different problems most often difficulty in hearing in environments with background noise [101]. These types of programmable hearing aids are currently available in market; however the setting can be changed manually [102]. Two of the most promising techniques introduced for audio classification were artificial neural networks (ANN) and hidden Markov models (HMM) [103]. A three-layer (one hidden layer) feed-forward perception with a variable number of hidden nodes type network was used in the work and it was trained using back-propagation [104]. Hidden Markov models were stochastic signal models, mainly based on Markov chains [105]. Although, many previous works have tested many possible features for this application [106], the most appropriate feature vector was dependent on both the classes [107] and the classifiers. Now, the aim of a system dealing with human-robot interaction is that the robot finds a person speaking in an area and goes to the speaker while the robot avoids static obstacles using mapping data obtained before. For this, the system acts like human especially when turning its head after someone calls. Now this intelligent and active system for Human-Robot interaction based on sound source localization has been discussed in this papers[108-110].The development of an 8-channel,real time, vibrotactile vocoder based on a TMS320C25 digital signal processing chip and by using FET spectral analysis technique is shown in [111].

6. Vibrotactile Sensing Elements for Artificial Skin Applications:

The skin is the largest stretched sense organ in human body. The replacement technique of artificial skin was from ancient times and the traditional method of replacement of skin was generated either by using skin from other parts of patients body or from a different person. Although, the disadvantages of the first technique was unavailability of ample skin and of the later technique was fear of being infected, lots of researches have been put on this artificial skin field and the consolidated studies about artificial skin have grown important eruditions about this field. The development of artificial skin surface ridges for incipient slip detection in pursuit of elucidating the mechanism of static friction sensing has been discussed by Yoji Yamada et all[112]. Now for the development of this plan it was determined to generate vibrotactile sensing capabilities on a skin tissue that has softness like human. Earlier, in a study about parallel change in the grip, the load forces was observed during precision grip of an object and the ratio between the two forces was adapted to result in the static friction coefficient between the finger skin surface and the object. This examination process was done by Johansson et al[113]. A tactile sensor system capable of detecting the incipiency of slip between an object and the sensor surface was proposed by Gaetano et al. by using the normal and shear stress information from arrays of PVDF transducers[114].The effectiveness of incipient slip detection more early using the peripheral slip signal from accelerometers which were mounted on a curved soft surface was
discussed by Tremblay et al.[115]. However, better shape and structure of the skin surface ridges with vibrotactile sensing elements could be designed and the dynamic response of human finger skin for tactile receptors focusing on the effect of epidermal ridges using FE analysis served as a background of the strategy of design[116].

7. Conclusion: During the last few decades, lot of clinical and research works have been carried out which points towards the future development of prosthetic studies. Our overview study is an effort to visualize all the recent works based on human prosthetic sense organs as much as possible. This overview is not intended to be an exhaustive survey on this topic, though a sincere effort has been made to cover all the recent works as much as possible and any omission of other works is purely unintentional. Future works aims at making smarter prosthesis, by better integrating the state of art- neuroscience with the state of art- engineering, medicine, computer and social science.

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