Determining Personal Credit Rating through Voice Analysis: Case of P2P loan borrowers

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Abstract

Fintech, which stands for financial technology, is growing fast globally since the economic crisis hit the United States in 2008. Fintech companies are striving to secure a competitive advantage over existing financial services by providing efficient financial services utilizing the latest technologies. Fintech companies can be classified into several areas according to their business solutions. Among the Fintech sector, peer-to-peer (P2P) lending companies are leading the domestic Fintech industry. P2P lending is a method of lending funds directly to individuals or businesses without an official financial institution participating as an intermediary in the transaction. The rapid growth of P2P lending companies has now reached a level that threatens secondary financial markets. However, as the growth rate increases, so does the potential risk factor. In addition to government laws to protect and regulate P2P lending, further measures to reduce the risk of P2P lending accidents have yet to keep up with the pace of market growth. Since most P2P lenders do not implement their own credit rating system, they rely on personal credit scores provided by credit rating agencies such as the NICE credit information service in Korea. However, it is hard for P2P lending companies to figure out the intentional loan default of the borrower since most borrowers' credit scores are not excellent. This study analyzed the voices of telephone conversation between the loan consultant and the borrower in order to verify if it is applicable to determine the personal credit score. Experimental results show that the change in pitch frequency and change in voice pitch frequency can be reliably identified, and this difference can be used to predict the loan defaults or use it to determine the underlying default risk. It has also been shown that parameters extracted from sample voice data can be used as a determinant for classifying the level of personal credit ratings.

Keywords: Fintech, P2P lending, Social Lending, P2P Loan Default, P2P Credit Rating.

This version includes a concrete analysis of the potential risk of loan default of P2P lending companies in South-Korea, and propose a personal credit rating method using voice analysis through the phone conversation data.

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1. Introduction

Financial technology (hereinafter Fintech*)* is growing rapidly around the world since the 2008 economic crisis hit the United States. Compared to traditional financial services, Fintech companies are striving to secure a competitive advantage over existing financial services by providing efficient financial services utilizing the latest technologies [1]. Since the 2000s, Fintech innovation has been taking place in various fields such as payment, security, financing, and asset management in the global market. To this end, ecosystem-centered Fintech innovation, which is dominated by platform operators, has a competitive advantage [2]. The platform means that many people can easily access and use it for various purposes [3]. In the digital environment, the platform has a huge network effect, so it has become a minority oligopoly system. For this reason, it can only be applied to specific areas of the leading providers such as search engines like Naver or Google, communication platforms like KakaoTalk, and e-commerce providers such as Alibaba, G-Market, and Auction. In particular, the domestic P2P lending platform, which started to grow rapidly by the end of 2014, has continued to grow very steeply and now threatens the secondary financial market. However, as its growth rates have increased so too are potential risk factors also increasing. In addition to government laws to protect and regulate P2P lending, further measures to reduce the risk of P2P lending accidents have yet to keep up with the pace of market growth. The government has proposed P2P loan guidelines to prevent P2P loan accidents, but P2P financial loan information is not shared with financial institutions nor reflected in credit ratings used by credit evaluation agencies [4]. As a P2P lending company’s perspective, the critical factors for successful operation might be the deep screening of potential borrower’s credit risk in order to avoid borrower’s default. In order to avoid these risks, P2P lending companies not only uses personal credit score that was obtained from credit bureau, but also adopting new technologies such as big data analysis, psychometric test, etc.

Recently, P2P lending companies in Korea has faced challenges in managing its soundness and restoring consumer confidence as the delinquency rate has skyrocketed in recent years. The delinquency rate is showing a sharp rise every day as the number of past due loans increases as the market shrinks due to Covid-19, and the number of new transactions is decreasing due to the government's real estate regulation [5]. This may be because most P2P lenders do not implement their own credit rating systems and rely on personal credit scores that can be provided by credit rating agencies such as the NICE credit information service in Korea. However, it is hard for P2P lending companies to figure out the intentional loan default of the borrower since most borrowers’ credit scores are not excellent. In recent days, there has been a study that proposed an artificial intelligence-based P2P default prediction model using a P2P loan transaction database. However, this alone is not sufficient to suggest a way to proactively filter out potential defaulters. Therefore, the necessity of establishing a credit rating system of P2P companies has been raised. This study propose a method of establishing a P2P company's own credit rating system. In addition, as a construction method, it is proposed to use the results of the borrower's voice analysis. In more detail, this study analyzed the characteristics of voice conversations with loan agents in the P2P lending industry, suggesting the possibility of application of potential borrowers' voices for personal credit score determination.

2. Related Work

According to data analysis by Accenture, investments in Fintech ventures surged in 2019 in most major markets such as the United States and United Kingdom. In particular, growth in emerging markets such as India and Brazil has been remarkable [6]. P2P lending industry can be regarded as a sector of Fintech. According to Foundation Capital, which is a venture capital firm, the current market size of the global P2P lending industry is growing by more than 100% annually and is expected to grow to a maximum of $1 trillion by 2025 [7]. Although the popularity of P2P lending is worldwide, it stands out noticeably in Korea. According to the Korea P2P Financial Platform Association, the number of P2P lending companies increased from 10 in June 2015 to 240 in March 2020 [8]. The domestic P2P loan market is growing rapidly by word of mouth, allowing borrowers to get loans at a relatively low interest rate even with a poor credit rating [9]. In addition, the high smartphone penetration rate and fast mobile communication environment in Korea have greatly changed the pattern of mobile application users. Whether trading stocks, modifying investment portfolios or simply checking bank balances, users of mobile applications can easily handle most financial issues online. It means that businesses and financial firms cannot succeed without the right Fintech services are in place [10].

After the 2008 global financial disaster, many researchers have predicted that the P2P lending industry will emerge as one of the most innovative financial services [11]. However, most of the research to date has focused on the role and impact of social networks in the P2P loan industry [12]. In addition to social networks, there has been research on important factors influencing funding success and default rates. These factors include characteristics of the lender, demographic information, financial strength, credit rating and effort metrics [13-15]. Literature studies on P2P loans in Korea are even harder to find. Most of the studies in Korea are related to the analysis of the success and failure factors of loan repayment, or the establishment of regulations. The U.K. Trade & Investments (UKTI) has defined the Fintech industry in two categories: traditional Fintech and emergent Fintech [16]. Generally, Fintech companies are start-ups, said by McAuley [1]. However, some scholars have argued that Fintech companies should not be limited to start-up companies [17]. Investopedia clarifies this argument: “Since the end of the first decade of the 21st century, the term has expanded to include any technological innovation in the financial sector, including innovations in financial literacy and education, retail banking, investment and even crypto-currencies like bitcoin” [18].

2.1 Traditional Fintech vs. Emergent Fintech

Traditional Fintech referred to a market participant commonly recognized as a facilitator, typically a large, existing technology vendor supporting financial services sectors such as Infosys and FirstData. These traditional companies operate according to an established revenue model that tends to use cost-per-transaction, asset ratio, or license fees. Other traditional financial services companies, including banks, can become Fintech players by leveraging Fintech to improve products and services to their customers. Emerging Fintech companies are market participants who are disrupting and innovating companies that do not broker existing financial services companies or provide new technology solutions that meet existing requirements such as Transferwise, Zopa. [16].

2.2 Fintech Areas

Fintech has been used to automate five areas: 1) investments, 2) insurance, 3) trading, 4) banking services, and 5) risk management [19]. It depends on the market location. For solutions related to supported business processes, it can be subdivided into six financial services: 1) payments like digital wallets, 2) investments like P2P loans, 3) financing like crowdfunding, 4) insurance like risk management, 5) financial advisory like robo-advisor, and 6) cross-process like big data analysis. As explained, Fintech has created a whole new type of financial services, such as robo advisors, crowdfunding, and peer-to-peer loans [17].

2.3 P2P Lending Industry

P2P lending, also known as social lending, is a method of lending funds directly to individuals or businesses without the involvement of official financial institutions acting as intermediaries in the transaction. In other words, instead of lending their own funds to borrowers, P2P lending companies serve as facilitators to both the borrowers and investors [20]. Thus, compared to the regular lending process, P2P lending companies have the advantage of reducing operational costs because they offer their services entirely online. In addition, eliminating intermediaries by connecting lenders and borrowers directly online provides ease of use by simplifying the process as well as reducing costs [21]. These are distinctive competencies of P2P lending, which allows P2P lenders to earn higher returns than financial products offered by traditional financial companies. Also, borrowers can obtain loans at a lower interest rates than banks [22]. Since the P2P lending company that maintains the online platform charges a fee for both lenders and borrowers for successful transactions, the P2P platform itself is also profitable. Just looking at the advantages of P2P lending, it seems like a game that everyone wins. However, its ease of use and low cost entail more risks than traditional lending practices [23]. First, P2P loans are exposed to high credit risks. Many borrowers applying P2P loans have a low credit rating that is unable to get existing loans from prime banks. Therefore, the P2P lender must be aware of the default probability of the borrowers. Second, the current Korean government does not provide insurance or any form of protection to lenders in the event of a borrower's default [24].

The P2P lending industry in the United States began with the launch of Prosper in February 2006 [25]. The P2P lending market, which started in the United States, is spreading all over the world, especially in Korea. The number of P2P lenders in Korea has increased from 10 in June 2015 to 240 in March 2020. The 8 Percent that was founded in October 2014 and started business in June 2015 is considered one of the first generation P2P lending institutions in Korea. The 8 Percent has lent 6.5 billion KRW in 204 cases in the first year. Lee Hyo-jin, the chairman of the Korea P2P Finance Platform Association, said at the end of 2014, "Currently, the P2P lending market is at most 10-20 billion KRW, it will grow to over 1 trillion KRW within a few years" [8]. The P2P lending industry in Korea seems to have tremendous potential unlike traditional banks that require documents such as employment verification or income verification. Thus, P2P lending companies are very attractive to potential borrowers who have hard time getting loans from prime banks. However, as previously mentioned, it is hard for P2P lending companies to figure out the intentional loan default of the borrower since most borrowers visit P2P lending companies due to their low personal credit scores.

2.4 Personal Credit Rating of P2P Lending Company

As mentioned earlier, Korean P2P lending companies have achieved significant quantitative growth since 2014. However, recently, P2P lending companies in Korea are struggling to manage their soundness and restore consumer confidence as the number of overdue loans has surged since the coronavirus outbreak. Therefore, many Korean P2P lenders are building their own credit rating systems to detect potential defaults by borrowers in addition to personal credit scores provided by large credit rating agencies. On-Deck Capital, founded in 2007, is a U.S. listed global online small business lending company. On-Deck has developed a technology that can analyze the creditworthiness of a loan applicant in an instant by considering bank transaction details, cash flow, creditworthiness, and comments and ratings on social media [26]. According to a report by KB Financial Management Research Institute, a case of analyzing the personality of an individual through question and answering and converting it into credit score to measure the ability to repay loans is being used [27]. In fact, this credit rating, developed by VisualDNA in the UK, is a system that lends money based on the results after testing for about 15 minutes without looking at credit scores, financial records, collateral, and loan history. Loan applicants can select the picture closest to their answer to questions such as 'how do you feel when you are alone' or 'what role do you want to play in the play' on VisualDNA's homepage [28]. As a Korean P2P lending company, ‘Ernest Fund’ is known to have applied this personality test technique to the Korean situation and used it in their own credit rating system [29].

Statistical-based mathematical methods are used in traditional speech recognition and classification. However, deep learning, which models human cognitive processes, is widely used in speech recognition these days and is also applied to credit rating systems. K. Yoo studied a method to recognize human screams using deep learning and implemented it as a system [30]. He applied a convolutional neural network (CNN), a type of deep learning, to accurately recognize screams among various noise sounds in the surroundings to achieve the research objectives. Wang, Han, Liu and Luo proposed a consumer credit scoring method based on the attention mechanism LSTM using data on the online operation behavior of borrowers. LSTM is a new application of deep learning algorithms [31]. Ha and Nguyen from Vietnam constructed a credit score model based on deep learning and feature selection to assess applicants' credit score from the applicant's input characteristics [32]. Deep learning is currently an active field of research and is a powerful classification tool that successfully solves classification problems in multiple areas. This deep learning technology is expected to be applied much more in evaluating personal credit scoring in the future.

3. Mobile Applications for P2P Lending Companies

Mobile app refers to application software optimized for mobile devices so that individuals can transmit/receive various data, video, and audio information while carrying or moving around, such as smartphones, tablet PCs, and smart watches [33]. Representative mobile apps include social media apps such as Facebook, Twitter, and Instagram, video service players such as Youtube and Netflix, music players such as iTunes, Vibe, Bugs, and calls and text messages such as Skype, Kakaotalk, and Line. The mobile app is designed with the needs and limitations of the device and utilizes all the special features of the device. Gaming apps, for example, can utilize the iPhone's accelerometer [33]. Mobile apps are developed based on the standard platform of the mobile operating system. Apple uses iOS and Google uses Android as the standard platform. These mobile apps are provided through the app stores of each business operator that provides the app, and a number of apps are provided for free, and most of the free apps generate revenue through app advertisements. The mobile app requires an installation process and has a limiting factor that it runs on a specific device, but it can be said to be advantageous over the mobile web in terms of speed and security [34].

The first mobile app for P2P lending was developed by ‘Lending Robot’ and launched in April 2016. According to ‘Lending Robot’, the app tracks the overall status of an account and provides a description of the portfolio. The app showed that 30% of customers log in multiple times a week and some log in once a day. The peculiar thing is that about 20% of users of this app were already using the ‘Lending Club’ website to log in from their smartphones, so the mobile app was naturally added to the service. Therefore, Lending Club's P2P loan product investors can now manage their portfolios and investments through a new mobile app powered by a 'Lending Robot'. [35]. However, most of the newly developed P2P mobile apps such as lending robots were developed mainly for investors rather than lenders. In other words, investors can benefit from frequent app usage because they use the app repetitively. However, the goal is to deposit and use the tools they provide and have companies invest according to defined investment criteria instead of direct loans. This is probably why mobile apps for borrowers were not developed on the platform, but some third parties developed apps with implicit approval from companies [36]. In Korea, the first mobile app for P2P lending was launched by ‘Honest Fund’ in the form of a web-app, an existing web-based platform, in April 2016, which was able to provide only basic product information to both borrowers and investors. Therefore, it can be said that the first-generation mobile app of Korean P2P lending companies was not very different from the early mobile app environment of the United States [37]. However, most mobile apps for P2P lending companies in Korea does not facilitate with their own credit rating systems. As previously stated, since the first P2P lending company in Korea started business at the end of 2014, the P2P lending market is growing rapidly. Despite this rapid growth, few P2P lenders have developed their own credit rating system as they are still inferior to existing financial institutions in terms of capital. Also, existing financial institutions are reluctant to share personal credit information, conscious of their growth [17].

According to recent reports, the P2P lending companies are under surveillance due to soaring delinquency rates and investment fraud charges. Over the past few years, the rate of delinquency or overdue loans has snowballed in the P2P lending sector in Korea. According to the Korea P2P Finance Association, the average delinquency rate of 45 P2P lenders as of the end of January 2020 was 9.32%, up from 8.43% in the previous month. By comparison, the average delinquency rate at the end of 2016, when P2P was first introduced in Korea, was only 0.42% [38]. Therefore, it can be said that it is necessary to develop their own personal credit information system that can filter out intentional loan defaults of the borrowers to P2P lending companies. As described above, this study attempts to propose a method for developing a personal credit rating system that can predict defaults using the voices of borrowers.

4. Characteristics of Sound & Voice

The human voice is a key element for the speech delivery. People, in these days, are trying to deliver their intent of speech clearly to others. Through the analysis of the voice, the different characteristics of the borrowers can be extracted from the phone conversation with the loan agent. The extracted characteristics need to be parameterized in order to be used as determinants for classifying the level of personal credit ratings. For this study, the voices were collected from those who default on their loans in an early stage after they get a loan in order to figure out if the default is intentional or not. Then the voices were analyzed using voice parameterization technique to figure out the characteristics of loan defaulters to examine the applicability of the voice into personal credit ratings.

As stated above, this study utilizes the potential borrower's voice conversation with the loan agent in order to minimize the risk of the default. The basic features for sound and voices are as follows.

4.1 Sound

In physics, sound is a vibration that propagates through air or water as mechanical waves of pressure and displacement that are usually heard. In physiology and psychology, sound is defined as the brain accepting and recognizing these waves [39]. In short, sound is a form of energy that enables human to hear. In general, humans can detect sound in the frequency range of about 20 Hz to 20 kHz, while animals are known to have a different range than humans. Sound travels in the form of waves, which can be described by five characteristics: wavelength, amplitude, time-Period, frequency and velocity. Waves are created by vibrations of particles of a medium passing through them. There are two types of waves: longitudinal and transverse waves. A longitudinal wave is a wave in which particles in a medium vibrate back and forth in the 'same direction' in which the wave moves. The medium can be a solid, liquid, or gas. A transverse wave is a wave in which particles in a medium oscillate up and down at 'perpendicular' to the direction of travel of the wave. These waves are produced only in solids and liquids, but not in gases. Therefore, a sound wave is a longitudinal wave [40]. One thing many people do not realize is that sound waves have physical properties and are therefore affected by the environment in which they occur. For example, sound cannot be produced in the vacuum of space because there is nothing to vibrate and produce a sound wave in a true vacuum [39]. The two most important physical properties of sound are frequency and amplitude. Frequency is the speed at which sound waves vibrate and determines the pitch of the noise. Pitch is the quality of sound experienced as a function of the frequency or speed of vibrations and represents the perceived high or low degree of a tone or sound. High-frequency sounds have a higher pitch, such as a flute or a bird chirping, and low-frequency sounds have a lower pitch, such as a tub or a big dog barking. Amplitude is the size of a sound wave, a property of a sound that affects the perceived loudness of the sound. The amplitude of a sound wave can be thought of as the strength of the vibrations as they travel through the air, and it determines the perceived loudness of the sound [40]. There are six experimentally separable ways of analyzing sound waves, and they are pitch, duration, volume, timbre, sound quality, and spatial position [41].

4.2 Voice

A voice is a sound produced by the vocal cords of a person, and it is a wave of air originating from the vocal cords. The length of the neck, the length of the nose, etc., the waves of air that can be produced are to some extent determined, so just as no two people have the same face, each person's voice is different because the voice resonates with the face. This is called a voiceprint [40]. In general, the mechanisms that produce a human voice can be divided into three parts. Vocal folds and articulators in the lungs and larynx. The lungs must create the proper airflow and pressure to vibrate the vocal cords. The vocal cords, also known as vocal folds, are 2 bands of smooth muscle tissue found in the larynx. The larynx is set in the neck at the top of the trachea. The vocal cords vibrate and air passes through the cords from the lungs to make the sound of the voice [41]. The tone is known as the color of the voice. Every voice has a certain color that can be described as warm, dark or arrogant. Also, the tone of the voice can be modulated to suggest emotions such as surprise, happiness or anger [40]. Two singers singing the same song in the same key may sound different because of their tone. Human speech language dynamically modulates specific parameters of the laryngeal speech source in a consistent way [42]. The most important parameters of communication or phonetics are the pitch of the voice, which can be determined by the frequency of vibrations of the vocal folds, and the degree of separation of the vocal folds called vocal fold adduction. The ability to rapidly change the abduction/adduction of the vocal folds has a strong genetic component. This is because, in addition to covering the epiglottis, vocal fold adduction has a life-saving function that prevents food from passing to the lungs. As a result, the muscles that control this movement are one of the fastest in the body [43].

4.3 Speech Production Model

According to Wikipedia, "the source-filter model represents a voice as a combination of a vocal cord-like sound source and a linear acoustic filter, the vocal tract. Although only an approximation, the model is widely used in several applications such as speech synthesis and speech analysis due to its relative simplicity" [44]. According to the source-filter model of speech generation, the complex wave actually coming out of the speaker's mouth depends on two things. The first is the source which is the glottal wave. The second is the filter, which is amplification and de-amplification imposed by the frequency response curve of the vocal cords. Assumptions are required when using the source-filter model, and an important and frequently used assumption is the independence of source and filter. In this case, it is more accurate to call the model an independent source-filter model [45]. The development of the model is largely due to the early work of Gunnar Fant. Others, notably Ken Stevens, have also contributed significantly to the acoustic analysis basic models of speech and speech synthesis [41]. In the implementation of the source filter model of speech generation, the sound sources or excitation signal is often modeled as a periodic sequence of impulses for voiced speech and white noise for unvoiced speech. The vocal cord filter is approximated by the electrode filter in the simplest case, where the coefficients are obtained by performing linear prediction to minimize the mean square error of the speech signal to be reproduced. The convolution of the excitation signal with the filter response produces a synthesized speech [42].

5. Generating Voice for Analysis

A person's voice allows for the easy communication of information between people or between people and machines. Voices are generated through the human vocal organs and then disseminate into the air before eventually disappearing. At least in the present day and age, voices remain an individual characteristic of the people who create them. Additionally, voices sound similar but each voice possesses its own unique characteristics based on an individual's vocal organs, linguistic characteristics, personality, health, and psychological state [45]. When voices are analyzed, similar features are left in the form of sounds which have meanings in language, and non-similar features are caused by a variety of different causes. As people's voices are easily used for communication, IT technologies have been developed to record voices or to transmit them far away. Nowadays, by analyzing voice information, machines can perform the commands of a person, record information, judge psychology, and set operative directions [46]. The block diagram in **Fig. 1**. represents the flow and movement of information from the speaker to the listener. The average person undertakes this process through a number of exercises and habits to create voices, which are then easily delivered through the vocal organ, turned into vibrations, and then heard and analyzed by the ear to catch the meaning of sounds. All this takes place in a very short time period [47].

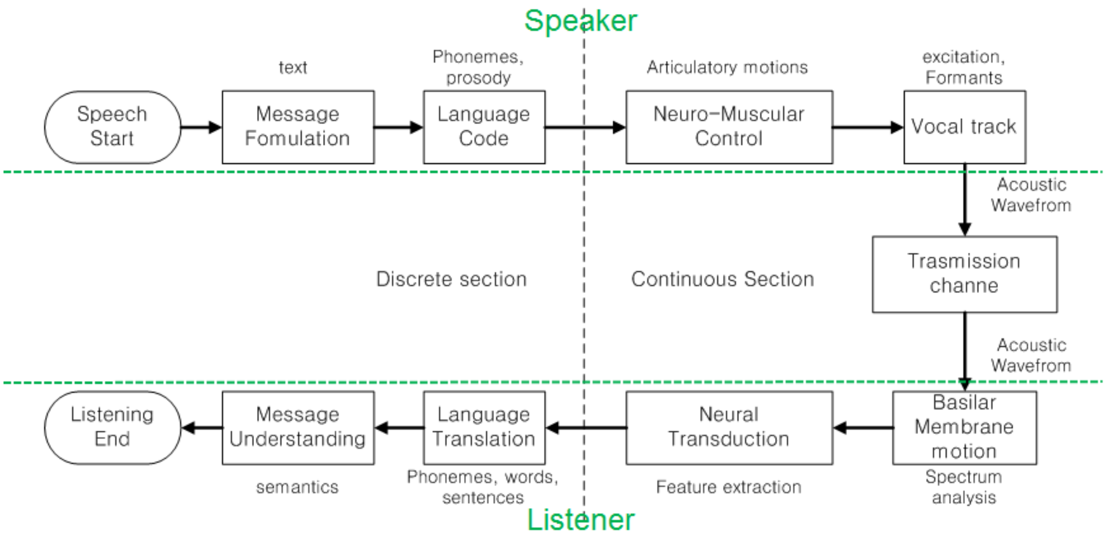

Fig. 1. Information flow from speaker to listener [47]

Voices have parameters that give them different and unique characteristics in different individuals. This is because the forms and characteristics of vocal organs are different, just like the face of each individual is different. In addition, vocal habits caused by an individual's social life, linguistic structures formed by commonly used vocabulary, and regional linguistic characteristics can all also be classified. Additionally, data from voice variations caused by an individual's health and psychological conditions can also be extracted and analyzed. Indeed, voices contain more than a hundred additional features that can be analyzed and identified to convey meaning through voices, as well as to identify health and psychology, and to judge the authenticity and reliability of a speaker [48]. A voice generation model can not only computerize speech and sound generation processes, but also analyze sounds heard by the ears. Speech is divided into voiced and the unvoiced sounds according to the principle of voice generation and assumed to be an excitation source. The sound or excitation source is divided into the impulse train and vocal chord model for voiced speech, and the white sound and vocal cord model for unvoiced speech that use the thickness, length, and the stenosis degree and stenosis timing of vocal tracts [45].

People use financial institutions for a variety of reasons. The basic function of finance is to enable the three major entities of households, businesses, and governments to secure necessary funds and manage surplus funds through transactions. The credibility or lack thereof of individuals and institutions in the financial sphere is very important information. The criterion for assessing credibility includes evaluating past financial performance and the form of past transactions, what kind of credit a bank has, if any, and assessing the amount and degree of risk associated with a bankruptcy. This study aims to develop a personal credit rating scale through voice analysis to apply to P2P financing in today's rapidly developing market. People try to speak well for various reasons. Most importantly they are trying to transfer their intentions in various speeches, personal conversations, sales, and even job interviews, and to clearly communicate intended information [48]. The voice can also be used as a measure for evaluating individual credit if voice analysis can successfully extract various analytical features and create a measure of the credibility of the voices [45].

6. Data Collection and Analysis

6.1 Data Collection

In order to obtain data for this study, the participating researchers were allowed to use the recorded telephone consultation files of a loan counselor and borrowers from a domestic savings bank company (S-Capital). It was made clear, by way of a verbal commitment, that this information would only be used for research purposes. Data for the study were the telephone counseling files before the loan approval of borrowers who had defaulted within 3 months after deliberate delinquency, and the consultation files after delinquency and deliberate bankruptcy. A sound engineer analyzed the characteristics of the voices before and after a person defaulted. Based on the results obtained from above process, this study searched for ways to apply them to a credit evaluation system for approving loans in the future. The method of voice analysis was based on pitch, formant, and the speaker’s dependency and independency, which in turn was based on the rate of utterance of the speaker.

In this process, however, the recording of a phone conversation between a loan counselor and a borrower is quite long, which is about 30 minutes. Therefore, the answer to prove the identity of the borrower, such as the borrower’s name, date of birth, address, etc., which is routinely asked by the loan consultant, was not included. In addition, for the convenience of analysis, the answers that were later found to be false during the Q&A process between the loan counselor and the loan applicant were first selected and analyzed. Again, the target of the analysis was loan defaulters, and the sound of the part where they answered falsely to the loan counselor's question was first analyzed. By applying the same process as above to the sounds that the defaulters answered as true, we tried to find the difference by comparing the two sounds, the true answer and the false answer.

6.2 Data Analysis

To evaluate voice reliability, Voice data was recorded at 11 kHz by telephone, the voices were processed by using a 300-4200 Hz band pass filter, quantized by 16 bit per sample. Voice data was analyzed for fifteen men and women generally aged in their 40s and 50s.

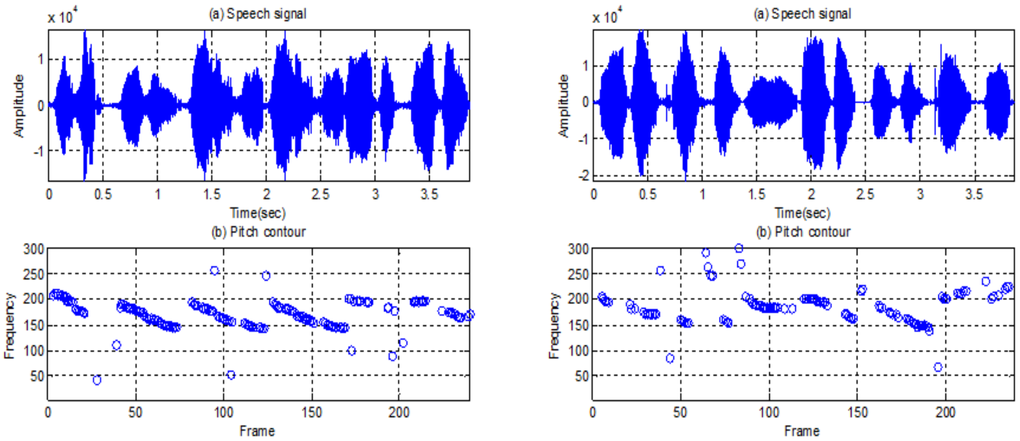

Fig. 2. Waveform and pitch analysis result according to reliability parameter change

Fig. 2 shows the parameters for evaluating the reliability of voices according to changes in credit ratings. The changes in credit ratings were compared between the voices in the loan review process and the voices in default situations after the loan. In particular, the characteristics of the same vocalist's 'yes' during vocalization were collected and analyzed. As a result, the rate of change of the pitch before and after the default has changed as seen in **Fig. 2**.

Fig. 3 and **Fig. 4** show the results of the voice waveform and pitch analyses, that is to say the results of analyzing the parameters using pitch change and pitch perturbation rate to determines the speaker's changed credit situation. As a result, it can be seen that there is a large difference in pitch variation and perturbation in situations where the bankruptcy is suspected or not suspected. For comparison, the changes in the pitch indicated by the circles in **Fig. 3** are closely analyzed. The analysis confirms that the pitch change degree of **Fig. 3** is constant, which means that the voice is monotonous and the change is small.

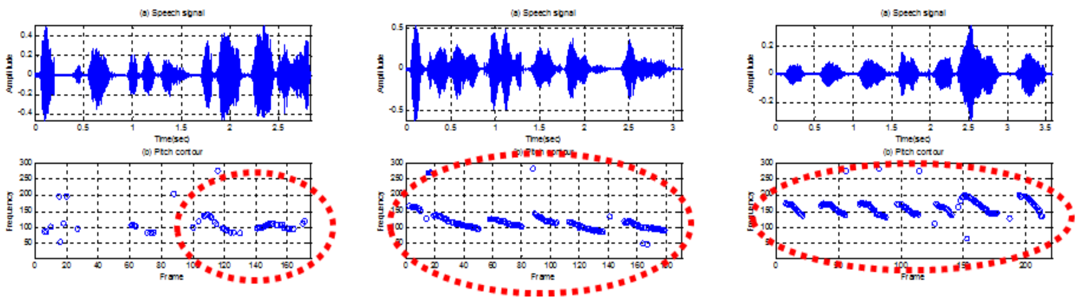

Fig. 3. Predictive pitch analysis results – 1

In **Fig. 3**, it can be seen that the degree of change is larger than for the suspicious voice. In **Fig. 4**, the number of pitch changes is larger than for the other voices though it is not easy to confirm with the naked eye. This analysis can determine whether a default is suspected or not by measuring the change in pitch and the change in pitch dispersion against time, and judging whether the change exceeds the value or not. In particular, it was confirmed that when the speaker's subordinate analysis was performed, the pitch dispersion of the time with time, the change occurred as time passed and the psychological change was severe.

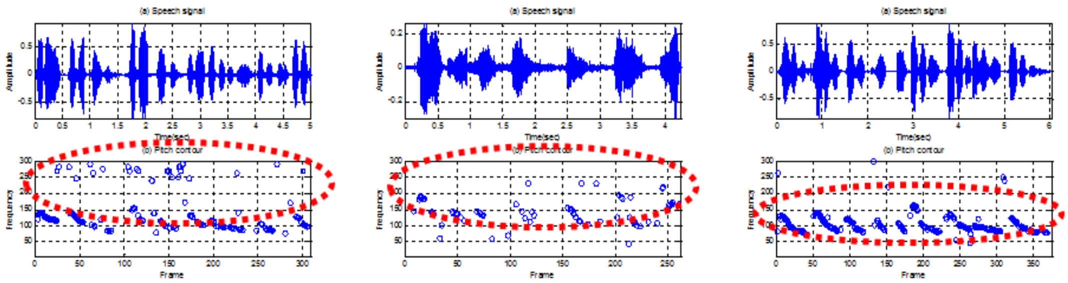

Fig. 4. Predictive pitch analysis results - 2

7. Conclusion

A person's voice contains various additional information as well as communicating information. The voice contains more than one hundred different features besides the basic function of the communication via voices. It is a common method to analyze this voice by separating it into an excitation source and a wave filler source in consideration of the generation process. The excitation source can be analyzed with the application of vocal cord model, and the wave filter source with vocal tract. The voice is the output of a time-varying system that changes over the time. However, the changes do not occur very rapidly nor regularly over the time. In addition, between changes and changes, similar features can be found with approximate cycles.

By analyzing these voices, much additional information such as health, psychology, and situation of people can be extracted and judged. This study examined the parameters which can evaluate the credit worthiness of people through voice analysis. This study have obtained the parameters necessary for credit evaluation through voice analysis of those who are directly involved in the loan in relation to credit and reliability. In order to evaluate the credit rating, the pitches of the voices of a person who had no abnormality of credit and the person who had a problem of credit were analyzed and an experiment was carried out to quantify the difference in the voices of two kinds of people. The results of the pitch analysis showed that the voice changes and differences before and after the bankruptcy was parameterized according to change rate of the pitch and the pitch dispersion in the voice of speaker’s independence and subordinate analyses. Therefore, it is possible to evaluate credit by extracting credit parameters through voice analysis, although it is problematic to evaluate all credits by voice.

There were some restrictions in conducting the research. The loan counselor asks questions according to the company's manual when consulting with a customer over the phone. In this process, the loan counselor's questions contain company-specific tips to induce and detect the lies of the borrower. Therefore, the loan counselor's questions were allowed to be used for research purposes only, and were promised not to be publicly disclosed. However, it is said that an experienced loan counselor can recognize it intuitively with just the sound of ‘yes’ to the question. This study focused on research on whether the intuition of loan consultants can be grasped by speech analysis. Since the recorded content of telephone consultation was long, the conversations that were judged to be meaningless in the experience of the loan consultant, such as questions and answers to verify the personal identity of the borrower, were removed for convenience of analysis. However, for future research, it is necessary to utilize deep learning in the process of data analysis and introduce it to the consumer credit rating system.

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